A Structural Model of a Multi-Tasking Salesforce: Job Task Allocation and Incentive Plan Design

Minkyung Kim, K. Sudhir and Kosuke Uetake*
Yale School of Management
minkyung.kim@yale.edu, k.sudhir@yale.edu, kosuke.uetake@yale.edu

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The paper empirically explores questions of job task allocation (specialization versus multi-tasking) in the presence of task complementarities and how to combine outcomes across tasks (e.g., additive versus multiplicative) in compensation program design. To answer these questions, we develop the first structural model of a *multi-tasking salesforce*. The model incorporates three novel features, relative to the extant structural models of salesforce compensation: (i) multi-tasking effort choice given a multi-dimensional incentive plan; (ii) salesperson's private information about customers and (iii) dynamic intertemporal tradeoffs in effort choice across the two tasks. While the model is motivated by our empirical application that uses data from a microfinance bank where loan officers are jointly responsible and incentivized for both *loan acquisition and repayment*, it is more generally adaptable to salesforce management in CRM settings focused on customer acquisition and retention. Our estimation strategy extends two-step estimation methods used for unidimensional compensation plans for the multi-tasking model with private information and intertemporal incentives. We combine flexible machine learning (random forest) for the identification of private information and the first stage multi-tasking policy function estimation. Estimates reveal two latent segments of salespeople–a "hunter" segment that is more efficient on loan acquisition and a "farmer" segment that is more efficient on loan collection. Counterfactual analyses show (i) that joint responsibility for acquisition and collection leads to better outcomes for the firm than specialized responsibilities even when salespeople are matched with their more efficient tasks; and (ii) that aggregating performance on multiple tasks using an additive function leads to substantial *adverse specialization* of "hunters", where they specialize on acquisition at the expense of the firm, compared to the multiplicative form used by the firm.

Key words: salesforce compensation, multitasking, multidimensional incentives, private information, adverse selection, moral hazard

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1. Introduction

How should a firm allocate tasks among its sales employees in designing jobs? Should different employees specialize in different tasks, or should they be made jointly responsible for multiple tasks? The fundamental trade-off for firms in job design and task allocation across employees involves the efficiency gains through increased productivity from specialization relative to the gains in productivity from internalizing complementarities in productivity across multiple tasks.

If a firm chooses multi-tasking, a second set of questions arises: How should the firm measure performance on multiple tasks and weigh/combine performance across tasks in incentive based compensation plans? For example, should performance on the different tasks be combined additively or multiplicatively when determining overall compensation? MacDonald and Marx (2001) shows that when there are intrinsic complementarities in production across tasks, an additive compensation scheme can lead to *adverse specialization*, where the employee chooses to specialize on the task which is less costly to the employee at the expense of overall firm productivity. To address this problem, they recommend a multiplicative incentive scheme which makes employee incentives to be also complementary and thus ensure greater productivity for a given level of compensation.

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), who are responsible for both loan acquisition and loan collection. In our context, we specifically seek to answer the question of whether a sales person should be responsible for both acquiring new loan and collecting the loans, in 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, but harder to collect repayments. The question has parallels to the customer relationship management (CRM) literature, in which sales employees may either specialize or jointly responsible for customer acquisition and retention. Further, if indeed loan officers are responsible for loan acquisition and repayment, how should performance on these dimensions be combined overall for their incentives?

Answering the questions of job task allocation (loan acquisition and repayment) and compensation design (how to combine performance on the two tasks) requires that we address two additional challenges. The first is "private information" as salespeople have private information about their customers not available to the firm that impacts 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 may also lead to incentive misalignment 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 novel "dynamic inter-temporal 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, has to be concerned about the trade-off on future payoffs because such a customer is more likely to not repay the loans.

To address these questions, we develop and estimate the first structural model of a multi-tasking salesforce. The model incorporates novel features such as private information among salespeople and the inter-temporal trade-offs faced by the loan officer in effort allocation across the loan acquisition and repayment tasks. The model allows for salesforce heterogeneity in costs of performing the loan acquisition and loan repayment tasks. We then perform counterfactuals to answer three key research questions of interest: First, should the bank design sales jobs allowing different salespeople to specialize on loan acquisition and retention, or should salespeople have joint responsibility for both tasks. Second, if the firm chooses the multi-tasking design, should the performance on the two tasks be combined additively or multiplicatively? Finally, we consider the effect of job transfers that destroy the salesperson's private information on overall firm profitability by testing whether the positive effects on efficiency or the negative effects of incentive misalignment is greater.

We estimate the dynamic structural model using a two-step estimation approach. Our empirical strategy extends and adapts the estimation approach in Chung et al. (2013), which studies a unidimensional compensation plan with no private information, to a multi-dimansional compensation plan with private information. Similarly to Chung et al. (2013), we incorporate discrete unobserved heterogeneity in salesperson's cost of effort using the framework in Arcidiacono and Miller (2011) and Arcidiacono and Jones (2003). The model estimation has three key challenges: (1) inferring private information and incorporating its effects into salesperson effort choice; (2) estimating inter-related multi-tasking first stage policy functions for acquisition and repayment effort; and (3) mapping multi-tasking policy functions to structural parameters.

In the fist-stage, we infer loan types, which is not directly observable in the data. We exploit the ex-post realized internal rate of return (IRR) along with observable loan characteristics (e.g., loan terms) and loan officer incentives at the time of origination and over the period of the loan. More precisely, we develop a predictive model of IRR using the random forest machine learning algorithm, which allows us to predict IRR for each borrower under the situation that the salesperson's monitoring effect does not exist. Based on the predicted IRR, we classify borrowers into two types–high and low.

In the next stage, we estimate effort-policy functions for each task (acquisition and maintenance) and each borrower type (good and bad), and corresponding performance outcome functions. To allow a flexible relationship between the performance outcome and state variables, we employ the random forest algorithm. A challenge arises because performance outcomes may be correlated each other due to unobserved factors (even though we include various control variables). We address it by applying a 2SLS approach with suitable exclusion restrictions. We embed this additional step in the Arcidiacono-Miller type estimation strategy to estimate the multi-task policy functions with unobserved heterogeneity in the cost function. Finally, we forward-simulate to construct moment inequalities based on deviation from the observed actions as in the two-step estimation of dynamic models, e.g., (Bajari et al. 2007).

Our empirical setting is a microfinance bank in Mexico. We estimate the structural model of multi-tasking by loan officers at the bank using the data of salesforce performance and compensation data matched with the loans generated by these loan officers with information about loan characteristics and repayment outcomes. The detailed data about salesforce performance and matched loan repayment data allow us to infer the effort policy functions. For instance, the salesperson may not have incentive to put much effort for acquiring bad type loans when her existing loan portfolio consists of many bad type loans.

Further, the bank adopted a random transfer policy of periodically moving loan officers to different territories to remove potentially corrupt lending to risky borrowers. This provides exogenous variation in the level of private information of loan officers about customers, allowing us to evaluate how private information impacts acquisition and collection behavior by comparing the outcomes of those who are randomly transferred to a new territory versus those who remain in their territories.

Our structural model estimates show two distinct segments of loan officers—who are heterogeneous in terms of their cost of effort for loan acquisition and maintenance, and their costs for acquiring and maintaining good relative to bad loans. As shorthand (and consistent with the descriptive literature on salesforce management), we refer to the two segments as (i) a large "hunter" type segment—so called as they have relatively low acquisition cost and thus are more efficient at "hunting" for new customers and (ii) a smaller "farmer" type segment—so called as they have relatively low maintenance cost and thus 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 larger and easier to acquire segment of lower quality customers–thus more likely to indulge in moral hazard through adverse customer selection.

In the counterfactual simulations, we first compare specialization versus multi-tasking in job design. Since our estimates indicate that there is a hunter segment and a farmer segment, a natural "specialization" based job design is for the bank to allocate all acquisition tasks to the hunter segment, and all maintenance tasks to the farmer segment. We find that the firm is better off with multi-tasking—by making salespeople responsible for both loan acquisition and repayment. 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.

Given that we find multi-tasking is optimal relative to specialization, we next investigate how to combine performance on acquisition and maintenance for overall compensation. In particular, as motivated earlier in the introduction by MacDonald and Marx (2001), we compare the multiplicative incentive scheme (the current scheme) and the additive incentive scheme. MacDonald and Marx (2001), motivate the need for a multiplicative incentive structure to create task complementarities in incentives for the salesperson to avoid adverse specialization, where each salesperson allocates more effort on the task which is less costly to them. In our setting, acquisition and repayment tasks are complementary to the loan officer, even under an additive scheme. Hence it is not obvious if the firm should enhance the complementarity by implementing the multiplicative incentive scheme. Our counterfactual shows a nuanced tradeoff in the use of additive versus multiplicative combination of performance. While the multiplicative scheme helps the firm by preventing the hunter segment from focusing on acquiring new loans, especially bad ones (i.e. adverse specialization), it backfires with respect to the farmer segment, who now seek balance on the acquisition metric (at which they are inefficient) under the additive incentive scheme, end up acquiring more bad loans that end up being delinquent.

Finally, we discuss the role of the salesperson's private information about customers by simulating salesperson performance and profitability when salespeople do not have private information versus when they do. Our results show 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.

The rest of the paper is organized as follows. Section 2 describes the related literature and situates the current paper with respect to that literature. Section 3 describes the institutional setting and the data. Section 4 and 5 describes the model and estimation. Section 6 discusses the results. Section 7 concludes.

2. Related Literature

First, our paper is related to the theoretical literature on multi-task principal-agent model (See, e.g., Holmström and Milgrom (1991), Baker et al. (1994), Dixit (2002)). These papers point out that incentivising one dimension of the multiple tasks may lead to the agent shirking on other performance dimensions if other dimensions are not well measurable. Holmström and Tirole (1993) find that incentive schemes that reward immediately realized profit can lead agents to sacrifice the long-run profit. Hence, the principal needs to carefully consider multi-dimensional incentives design and/or job design. Godes (2004), for example, suggests division of labor for risk-averse salesperson who work on technologically substitutable tasks. A highly relevant paper to ours is MacDonald and Marx (2001). They consider the situation where the principal prefers the agent to spend efforts on the various tasks, while the agent prefers to spend efforts only on the less costly tasks, as in our setup. In such a case, the agent tends to engage in "adverse specialization."[1] They show that the optimal contract to avoid the adverse specialization has a multiplicative structure across tasks that makes tasks complementary from the agent's perspective. This idea is close to

[1] The argument is empirically supported in (Hellmann and Thiele 2011, Casas-Arce and Martnez-Jerez 2009, Drago and Garvey 1998). Among those, Agarwal and Wang (2009) and Agarwal and Ben-David (2014) exploit exogenous change in the compensation structure of a bank in the United States to show that sales incentives encourage loan officers to take excessive risk and increase defaults. To address this issue, they argue that incentives have to be complementary in terms of performance across the multiple tasks. Bracha and Fershtman (2012) do not find the evidence for distorting effect of the pay-for-performance scheme, when the overall performance and is determined by the combination of the two observable and contractible tasks.

the compensation plan that the bank we study employs, but their setup is inherently static, while we study a more dynamic situation.

Despite the large number of theoretical papers on multitasking, empirical papers that actually study multidimensional incentives is still scarce. Behr et al. (2017) study the loan officer behavior under a multidimensional incentive scheme which takes into account both loan acquisition and loan performance. They find that the contract is effective for stimulating overall greater effort to extend loans while maintaining loan quality. Our companion paper Kim et al. (2018) use the same data as the current paper show the evidence of the sales person's private information about customers by running a series of reduced-form models. They find that salespeople exploit their private information about customers and tend not to acquire low quality borrowers when they are under the pressure of low loan-quality performance. Hence, the multidimensional incentives make the sales person balance acquisition and maintenance and align the sales person's incentive with the firm's interest even with private information. In this paper, we further extend the literature beyond showing the evidence of private information and the role of multidimensional incentives. In particular, we develop a dynamic structural model of salesforce with multidimensional incentives to examine the role of private information and of incentive structure. Moreover, empirical papers on job design is still scarce despite a highly influential paper by Holmström and Milgrom (1991). An important exception is Baker and Hubbard (2003), which studies the effect of IT on asset ownership and job design in the truck industry. Our paper is one of the first papers in marketing that study how to design jobs across salesforce.

Another strand of the literature related to ours is the empirical papers on salesforce compensation. Early works on the salesforce compensation such as Coughlan and Narasimhan (1992) provide descriptive analysis of salesforce compensation data, while some recent papers empirically study the design of salesforce compensation by estimating a structural model of salesforce behavior in response to the incentive scheme (e.g., Misra and Nair 2011, Chung et al. 2013). These papers study unidimensional performance incentives, while we add to this literature by considering a multidimensional performance incentive. In CRM-type settings, salespersons are in charge of not only customer acquisition but also other activities to increase CLV. Hence, it is important to understand how to design multi-task incentives for salesforce.

3. Institutional Setting and Data

This section provides the details of our empirical setting and data. We highlight multiple responsibilities of a salesperson, incentivized by a multidimensional compensation plan, and the role of salesperson private information.

3.1. Institutional Setting

Our empirical context is lending at a Mexican microfinance bank. As is typical with microfinance, given the needs of the target segment, the loans are made without collateral on relatively small amounts (average amount is \$670), with high interest rate (average monthly rate is 7.3%), and short maturity periods (average length is 4.1 months). The average return of the loans is 5.0%, which shows that delinquency rate is very high as 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 to study multi-tasking because loan officers at the bank are jointly responsible for both loan acquisition and loan repayment, and their incentive compensation is tied jointly to performance on both dimensions. At the acquisition stage loan officers recruit borrowers through referrals or personal visits, accept loan applications, and then recommend loan terms to the bank. The bank uses public information about the borrower (i.e., a $1-5$ credit rating with 5 as best, constructed with data from an external agency) together with information in the loan application to set the interest rate. The bank gives 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).

The salesperson's compensation in the bank we study has two parts: salary and bonus. The salary (S_{jt} for officer j at period t) is solely determined by seniority, not performance, while the bonus (B_{jt}) depends on customer acquisition and maintenance performances. Acquisition performance is benchmarked against one's own past performance to create an acquisition index (Acquisition index A_{jt} is defined by $A_{jt} = N_{jt}/Q_{jt}$, where N_{jt} is the amount of new loans acquired by office 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 at period t, 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 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 them no bonus at all. Note that the multiplicative feature of the incentive scheme not only leads officers to balance effort between acquisition and maintenance in any given time period, but also introduces a dynamic trade-off between the immediate benefits of acquiring (possibly lower quality) customers to improve acquisition performance, and its future negative effect on maintenance performance.

Throughout a loan cycle, loan officers create relational capital with their clients and use it to obtain private information about their motives, needs, financial capabilities/liabilities, and outside options.[2] Salespeople are found to use such private information in loan decisions on top of hard information in the firm database (e.g., credit rating), because observables alone may not be sufficient to evaluate borrowers (Kim et al. 2018). Specifically, salespeople *abuse* it to maximize their payoffs at the expense of the firm, by acquiring lower-quality customers to perform well on the acquisition metric. We find that multidimensional incentives are critical to overwhelm the negative effects of such salesperson moral hazard and obtain sales productivity gains in CRM settings. For example, the customer maintenance 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 customer acquisition. The main takeaway is that salesperson private information is a key part that drives his/her acquisition and maintenance behaviors that affect each loan's profitability and eventually the firm's profitability.

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 to avoid the potential abuse of private information by loan officers, which could lead to 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

[2] In our setting, a salesperson can obtain *private information*, which is not observable to the bank, since 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 repayment dates or collect loans, she gets to know how good the customer is running a business, or if the customer is experiencing unexpected financial hardship, or if the customer recently borrowed money from other institutions.

timing is intended to prevent loan officers from engaging in strategic acquisition behaviors at the expectation of getting transferred.[3]

A (randomly) transferred salesperson takes over and monitors the loans acquired by the predecessor who left the branch. The transferred salespersons maintenance bonus does not depend on the loans he/she has collected in the previous branch, but solely depends on repayment outcomes of loans he/she took over after transfer. In our model of a multi-tasking salesforce behavior, continuing (i.e. non-transferred) salespeople have private information about loan profitability, while transferred salespeople are treated as those without private information. Using the random transfer policy, we will investigate the role of salesperson private information on the design of job assignment and incentive plan.

3.2. Data

Our data consists of two datasets: (1) salesperson-level data that contain each salesperson's characteristics and monthly performance and compensation, analyzed in previous empirical salesforce compensation literature and (2) loan-level transaction data that contains 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. Salespeople were removed from the final sample if their aggregate performance do not match with the compensation index (i.e., some of their loans that seemingly contributed to their bonus are missing in the data). The final data consists of 2,648 observations on 229 salespeople who managed 100,250 loans from January 2009 to February 2010 (14 months).[4]

Table 1 reports summary statistics of our panel data. Each salesperson belongs to one of the five rankings (from A to E, where A is the highest level). We observe 4.8% of the observations (salesperson-month) are transferred every month on average, and 22.3% of the salespeople experience at least one transfer during our observation window. Salespeople have worked for the institution for 25.5 months on average, and acquire 347,470 pesos

[3] We later show that whether being transferred is not correlated with salesperson characteristics such as tenure, the length of time since last transfer, or previous performance in the next subsection.

[4] We do not observe much salesperson's 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 in regular business during the period. According to the Wikipedia page on 2009 Flu Pandemic in Mexico, the outbreak strengthened a strain on an economy. Although the World Bank provided Mexico $205 million in loans for immediate and long-term assistance, the concern went up, leading to the pesos biggest tumble. Mexico drew on a $47 billion credit line from the International Monetary Fund. Food services sector within Mexico City experienced losses of over $4.5 million per day. With meat price has dropped 30% within Mexico and several export bans executed, the pandemic caused severe damage to the industry.

(about US$25,365 as of 2009) of new loans, have 888,300 pesos (about US$64,845 as of 2009) of loans in the portfolio and collect 666,700 pesos (about US$48,670 as of 2009) of past loans each month. The acquisition index benchmarked against the quota is 0.82 on average, and the maintenance index benchmarked against the amount of loans in the portfolio is 0.86 on average. In the end, their total bonus was 55% of their salary on average.

We observe 22.3% of the salespeople have gone through a random relocation at least once during the observation window, which leads to the average monthly likelihood of transfer to be 4.8%. The randomness of the transfer decision is examined in the appendix.

Table 1 Summary Statistics of Loan Officer Characteristics

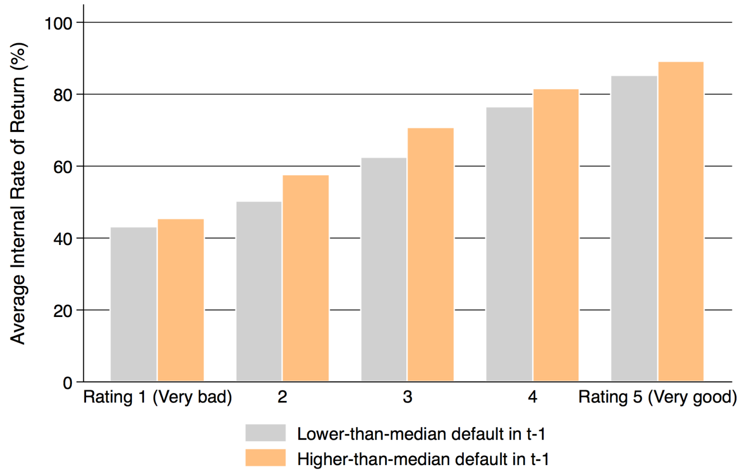
	N	Distribution			
Level	2352	E (29.85%), B (25.09%), C (24.74%)			
Transfer	2648	Yes (4.8%)			
Number of Transfer	229	0 (77.7%), 1 (21.0%), 2+ (1.3%)			
	N	Mean	SD	Min	Max
Tenure (months)	2352	25.51	21.69	1	143
New Loan Amount (1000 pesos)	2648	347.5	326	10	3066
Monthly Outstanding Loan Amount (1000 pesos)	2648	888.3	748.2	0	5209
Monthly Repayment Amount (1000 pesos)	2648	666.7	695.8	0	5052.7
Acquisition Quota (1000 pesos)	2648	429.2	492.8	13.2	2938.8
Acquisition Index	2648	0.82	0.42	0.02	3.19
Maintenance Index	2648	0.86	0.23	0	1.25
Bonus point	2648	0.55	0.3	0	2.35

Note that we do not know the exact formula for acquisition quota $Q_{j,t}$. According to the firm's policy, however, we know that a continuing salesperson's acquisition quota, which is used as a basis for 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 explore the transition of quota in the Estimation section.

3.3. Model-free Evidence

Before discussing the structural model in detail, we present some model-free evidence that motivates the development of our structural model. We note that Kim et al. (2018) present extensive reduced form analysis of the same data with appropriate controls/fixed effects for loan/borrower characteristics, time period and unobserved salesperson heterogeneity to show that (i) acquisition incentives lead to salesperson moral hazard (i.e., acquisition of riskier loans), (ii) maintenance incentives ameliorate the extent of moral hazard by disciplining salespeople to consider the future return of the acquired loans, and (iii) job

Figure 1 **Effect of Maintenance Incentives on Acquired Loan Quality**

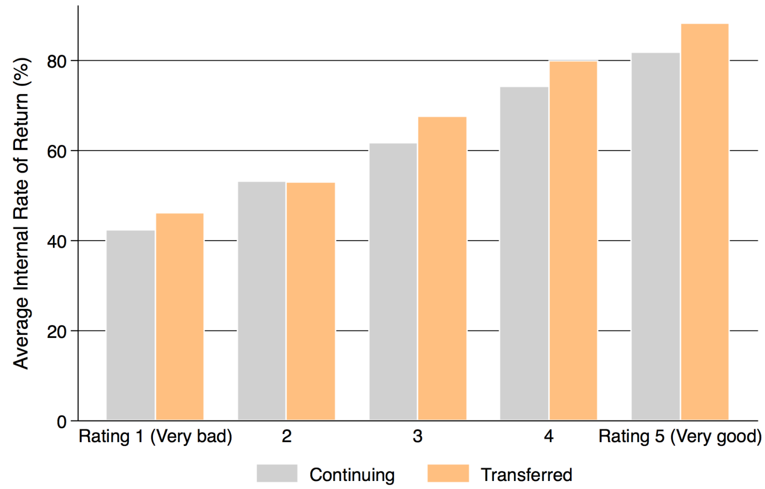


transfer moderates salesperson moral hazard at the time of loan acquisition (and prevents salespeople from collecting loans effectively). To avoid duplication of the analysis in Kim et al. (2018), yet keep the current paper relatively self-contained, we present only limited motivating model-free evidence to motivate two key assumptions underlying the structural model—effect of (i) multidimensional incentives (how maintenance incentives interact with acquisition incentives) and (ii) presence and effect of private information.

First, we show that for every observable level of rating, the quality of the loans newly acquired in period t is better when the default rate in the loan officer's portfolio at the end of the previous period $t-1$ is higher. See Figure 1, where we plot loans' public credit rating in the x-axis and average *ex post* annual Internal Rate of Return of loans acquired in period t on the y-axis. We median split the sample at each rating level based on share of loans under default in period $t-1$. Clearly, for rating the IRR of loans acquired is greater when the share of defaults is below the median. This indicates that the maintenance component of the incentive is able to motivate loan officers to acquire better quality loans, by reducing incentive misalignment, where loan officers acquire poorer quality loans to obtain loan acquisition bonuses, at the expense of firm profitability.

Second, we show that private information impact loan acquisition quality by exploiting the firm's transfer policy. Transfers generates an exogenous variation in private information within salespeople; so we compare the loan quality (IRR) of a transferred loan officer (i.e., without private information) to that of a continuing salesperson (i.e., with private information). Figure 1 plots the average ex post return of loans acquired by salespeople who

Figure 2 Effect of Private Information (Transfer) on Acquired Loan Quality



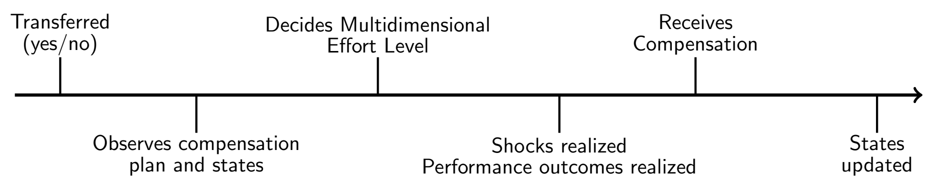
just got transferred to new branches and that of loans acquired by continuing salespeople in the same branch (i.e. salespeople who were not transferred at the beginning of the period) for each credit grade. The figure shows that transferred salespeople acquire better loans that generate higher ex post return on average than continuing salespeople. This suggests that salespeople on average use the private information to selectively bring in easier to acquire lower quality loans.

4. Model

Based on the model-free evidence, we now consider our dynamic structural model of the salesperson's multi-tasking behavior in the presence of private information. A salesperson in our model exerts her effort into acquisition and maintenance tasks in response to a multidimensional incentive scheme, which makes the salesperson inter-temporal decisions. Although borrower quality (likelihood of repayment) is not ex-ante publicly observable, salespeople can tell the private type once salespeople get familiar with the local demand conditions. A salesperson with private information about customer profitability has to take into account another dynamic trade-off of acquiring/maintaining each type of loans, i.e., acquiring easy-to-acquire, but riskier borrowers or acquiring hard-to-acquire, but less riskier borrowers. In our model, for simplicity, we assume that loans belong to one of the two types: good loans (ex ante profitable, and harder-to-acquire loans) and bad loans (ex ante unprofitable, and easier-to-acquire loans).

Figure 3 describes the timing of the model. First, the salesperson is randomly transferred from the branch she worked in the previous period to another branch. The salesperson then

Figure 3 Within-Period Timing of Salesperson Model



makes multidimensional effort decisions given the compensation plan and the state she is in. Outcomes of the efforts are realized subject to shocks and the salesperson receives compensation based on the realized performance outcomes. Finally, her states are updated. We will explain seven elements of the model to depict each stage of the timing: transfers, compensation plan, actions, state variables, performance outcome functions, state transitions, flow utility function and Bellman equation.

4.1. Transfers

Based on the firm's policy, the salesperson cannot predict whether being transferred or not. When the salesperson is transferred, she does not have any information about local demand and hence cannot tell the type of each borrower quality (good or bad). By contrast, continuing salespeople who are not transferred have perfect information about the type of each borrower. We assume that transferred salespeople become familiar with local demand will be able to tell the type in one month.[5]

4.2. Compensation Plan

The compensation is composed of two parts: (a) the acquisition index A_{jt} of salesperson j in period t, which depends on the salesperson's acquisition performance relative to his/her quota; and (b) the maintenance index M_{jt}, which rewards his/her loan collection performance. The final bonus is aproduct of the two metrics: $B_{jt} = A_{jt}M_{jt}$.[6] Recall that $A_{jt} = N_{jt}/Q_{jt}$, where N_{jt} is the amount of new loans and Q_{jt} is the acquisition quota. The quota-setting policy is described in section 4.4. Maintenance index is an increasing step function of the fraction of the loans that are collected on time: $M_{jt} = g(R_{jt}/O_{jt})$, where R_{jt} is the amount of repaid loans and O_{jt} is the outstanding value for j.[7] We denote the compensation plan as $\Gamma = \{Q_{jt}, g(.)\}$.

[5] We check the robustness of this assumption by varying the number of months it takes to get familiar with the local demand to 2 and 3 months.

[6] 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.

[7] We provide the details of the maintenance index in the appendix.

4.3. Actions

A set of actions that the salesperson can take depends on whether the salesperson has private information about loans (e.g., continuing salesperson) or not (e.g., transferred salesperson). The salesperson with private information can observe loan types and hence separately chooses acquisition effort for good loan ($e_{jt}^{A_G}$), acquisition effort for bad loan ($e_{jt}^{A_B}$), maintenance effort for good loan ($e_{jt}^{M_G}$) and maintenance effort for bad loan ($e_{jt}^{M_B}$).

The salesperson without private information cannot distinguish loan types and hence only decides total acquisition effort (e_{jt}^{A}) and total maintenance effort (e_{jt}^{M}). Then, depending on the population distribution of good and bad loans in each branch/period, the allocation of acquisition and maintenance efforts into good and bad loans is beyond the salesperson's control. In other words, with probability p_{jt}^{G}, e_{jt}^{A} is allocated to acquire good loans, and with probability $1-p_{jt}^{G}$, e_{jt}^{A} is allocated to acquire bad loans, where p_{jt}^{G} is the probability of a loan belonging to good loans in the branch that j works in period t. Salesperson j has a rational belief on the distribution of the type of loans in the market.[8] In the end, acquisition/maintenance efforts for each type of loans turn out to be $e_{jt}^{A_G} = p_{jt}^{G} e_{jt}^{A}$, $e_{jt}^{A_B} = (1-p_{jt}^{G}) e_{jt}^{A}$; $e_{jt}^{M_G} = p_{jt}^{G} e_{jt}^{M}$, and $e_{jt}^{M_B} = (1-p_{jt}^{G}) e_{jt}^{M}$, where e_{jt}^{A} and e_{jt}^{M} are j's decision variables.

4.4. State Variables

Each effort choice is affected by a set of state variables. For a salesperson without private information, state variables s_{jt}^{A} that determine acquisition effort e_{jt}^{A} include (a) the amount of outstanding loans (O_{jt}), (b) the amount of loans to be expired at the end of period t (E_{jt}), (c) acquisition quota (Q_{jt}), and (d) salesperson tenure (τ_{jt}). First, j considers the effect of acquiring new loans in period t on the maintenance effort she needs to exert from period $t+1$. The amount of outstanding loans (O_{jt}) and that of to-be-expired loans (E_{jt}), as well as the amount of loans acquired in period t, shift the volume of loans that j collects from the next period. Next, acquisition quota Q_{jt} directly affects e_{jt}^{A}. Tenure τ_{jt}, the number of months since j has worked for the firm, is a proxy for salesperson j's ability and knowledge, which enables her to change effort level. Maintenance effort e_{jt}^{M} is chosen as a function of (a) the amount of outstanding loans (O_{jt}), (b) the lagged amount of repaid loans ($R_{j,t-1}$), and (c) tenure (τ_{jt}). Since the compensation plan indicates that

[8] In our empirical specification, we compute the fraction of good loans among loans in each branch/period to construct p_{jt}^{G}.

maintenance performance is benchmarked against the amount of outstanding loans (O_{jt}), j considers O_{jt} in the choice of e_{jt}^{M}. The amount of repaid loans in period $t-1$ ($R_{j,t-1}$) enables j to be aware of the repayment likelihood of existing loans.[9] Tenure (τ_{jt}) represents j's ability and knowledge to do the maintenance task.

For a salesperson with private information, the information on loan types generates additional state variables to be considered. State variables $s_{jt}^{A_G}$ that determine acquisition effort for good loans $e_{jt}^{A_G}$ and $s_{jt}^{A_B}$ that affect $e_{jt}^{A_B}$ for bad loans include (a) the amount of outstanding good loans (O_{jt}^{G}), (b) the amount of good loans to be expired at the end of period t (E_{jt}^{G}), (c) acquisition quota (Q_{jt}), and (d) salesperson tenure (τ_{jt}).

The salesperson with private information takes into account the distribution of loan types among her outstanding loans because good loans and bad loans are not equally costly to monitor in the subsequent periods. Good outstanding loans O_{jt}^{G} and to-be-expired good loans E_{jt}^{G} affect the amount of good loans that j has to collect from period $t+1$ and are included as state variables. Maintenance effort for good loans $e_{jt}^{M_G}$ is chosen a function of (a) the amount of outstanding good loans (O_{jt}^{G} and O_{jt}^{B}), (b) the lagged amount of repaid good loans ($R_{j,t-1}^{G}$), and (c) tenure (τ_{jt}). First, salesperson j examines the amount of outstanding loans in both types (O_{jt}^{G} and O_{jt}^{B}) that constitute the benchmark for maintenance bonus in period t. Next, $R_{j,t-1}^{G}$ provides information on repayment likelihood of good loans that j maintains. Likewise, state variables $s_{jt}^{M_B}$ that affect maintenance effort for bad loans $e_{jt}^{M_B}$ include (a) the amount of outstanding loans by *loan type* (O_{jt}^{G} and O_{jt}^{B}), (b) the lagged amount of repaid bad loans ($R_{j,t-1}^{B}$), and (c) tenure (τ_{jt}). Table 2 summarizes the state variables for each action.

4.5. Performance Functions

We now link salesperson effort to acquisition and maintenance performance outcomes, based on which she gets compensations. We define the salesperson's acquisition performance outcomes as the amount of new good loans acquired by salesperson j in period t (N_{jt}^{G}) and the amount of new bad loans (N_{jt}^{B}). The acquisition outcomes are determined by the salesperson's acquisition efforts, exogenous shifters, and idiosyncratic shocks as follows.

$$\begin{aligned} N_{jt}^{G} &= e_{jt}^{A_G}(s_{jt}^{A_G}, s_{jt}^{\setminus A_G}; \lambda_{jt}^{A_G}) + f(X_{jt}; \beta_{jt}^{A_G}) + \epsilon_{jt}^{A_G}, \\ N_{jt}^{B} &= e_{jt}^{A_B}(s_{jt}^{A_B}, s_{jt}^{\setminus A_B}; \lambda_{jt}^{A_B}) + f(X_{jt}; \beta_{jt}^{A_B}) + \epsilon_{jt}^{A_B}, \end{aligned} \tag{1}$$

[9] Kim et al. (2018) finds that a salesperson changes maintenance effort depending on her lagged maintenance bonus ($M_{j,t-1}$). We use the lagged amount of repaid loans ($R_{j,t-1}$) here that directly affects the lagged maintenance bonus ($M_{j,t-1}$).

Table 2 State Variables

Effort Decision	Without Private Information: State Variables		With Private Information: State Variables	
Acquisition - Good ($e_{jt}^{A_G}$)	Endogenous	Outstanding amount (O_{jt}), To-be-Expired amount (E_{jt}),	Endogenous	Outstanding - Good (O_{jt}^{G}), To-be-Expired - Good (E_{jt}^{G}), Acquisition Quota (Q_{jt}),
			Exogenous	Tenure (τ_{jt})
Acquisition - Bad ($e_{jt}^{A_B}$)	Exogenous	Acquisition Quota (Q_{jt}), Tenure (τ_{jt})	Endogenous	Outstanding - Bad (O_{jt}^{B}), To-be-Expired - Bad (E_{jt}^{B}), Acquisition Quota (Q_{jt}),
			Exogenous	Tenure (τ_{jt})
Maintenance - Good ($e_{jt}^{M_G}$)	Endogenous	Outstanding amount (O_{jt}), Lagged Repaid amount ($R_{j,t-1}$)	Endogenous	Outstanding - Good, Bad (O_{jt}^{G}, O_{jt}^{B}), Lagged Repaid - Good ($R_{j,t-1}^{G}$),
			Exogenous	Tenure (τ_{jt})
Maintenance - Bad ($e_{jt}^{M_B}$)	Exogenous	Tenure (τ_{jt})	Endogenous	Outstanding - Good, Bad (O_{jt}^{G}, O_{jt}^{B}), Lagged Repaid - Bad ($R_{j,t-1}^{B}$),
			Exogenous	Tenure (τ_{jt})

where acquisition effort for good loans ($e_{jt}^{A_G}$) is a function of state variables for acquiring good loans ($s_{jt}^{A_G}$) and state variables for other tasks ($s_{jt}^{\setminus A_G}$), parameterized by λ_{jt}^{A}. Since efforts are jointly chosen, outcomes are jointly determined by all state variables.[10] The exogenous shifters denoted by X_{jt} drive the performance outcomes through $f(.)$ (parameterized by β_{jt}^{A}) independent of effort. The shifters X_{jt} include (a) salesperson tenure (τ_{jt}) that represents j's ability and knowledge in the task, (b) average acquisition quota in branch b where j works for, in period t ($\bar{Q}_{bt}$) that captures the branch-level market condition in period t. The average quota accounts for market conditions, since it depends on the cumulative acquisition performance up to period $t-1$ of salespeople in branch b, and captures the firm's expectation on the branch-level acquisition performance in period t. We add the interaction between τ_{jt} and $\bar{Q}_{t}$; and τ_{jt} and $\bar{Q}_{bt}$ to represent the differential impact of market condition on acquisition performance, depending on j's capability. The same claims apply to the acquisition performance outcome on bad loans. Finally, idiosyncratic shocks $\epsilon_{jt}^{A_G}$ and $\epsilon_{jt}^{A_B}$ such as unexpected market condition in each market/period, are not anticipated nor observed by salesperson j before the effort choices.

[10] For example, choosing the acquisition effort for good loans, j takes into account states that affect acquisition effort of bad loans ($e_{jt}^{A_B}$), 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, thus considers states that affect maintenance effort of each type of loans ($e_{jt}^{M_G}$ and $e_{jt}^{M_B}$) in the choice of acquisition effort for good loans.

In the same manner, we model the maintenance performance outcomes, defined as the amount of repaid good loans by salesperson j in period t (R^G_{jt}) and the amount of repaid bad loans (R^B_{jt}), as follows:

$$
\begin{aligned}
R^G_{jt} &= e^{M_G}_{jt}(s^{M_G}_{jt}, s^{\backslash M_G}_{jt}; \lambda^{M_G}_{jt}) + f(X_{jt}; \beta^{M_G}_{jt}) + \epsilon^{M_G}_{jt}, \\
R^B_{jt} &= e^{M_B}_{jt}(s^{M_B}_{jt}, s^{\backslash M_B}_{jt}; \lambda^{M_B}_{jt}) + f(X_{jt}; \beta^{M_B}_{jt}) + \epsilon^{M_B}_{jt}.
\end{aligned}
\tag{2}
$$

Maintenance effort for good loans ($e^{M_G}_{jt}$) depends on all state variables. In addition, the outcome is a function of exogenous shifters (X_{jt}) and idiosyncratic shock ($\epsilon^{M_G}_{jt}$). The same claims apply to the maintenance performance outcome on bad loans. Idiosyncratic shocks $\epsilon^{A_G}_{jt}$, $\epsilon^{A_B}_{jt}$, $\epsilon^{M_G}_{jt}$ and $\epsilon^{M_B}_{jt}$, which are not observed by j before the choice of efforts, are correlated with each other to capture the simultaneity in effort decisions and unexpected market condition that affects 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 (τ_{jt}); and the amount of outstanding loans in total (O_{jt}) or by type (O^G_{jt} and O^B_{jt}) evolve deterministically as follows:

$$
\begin{aligned}
\tau_{j,t+1} &= \tau_{jt} + 1, \\
O_{j,t+1} &= O_{jt} + N_{jt} - E_{jt}, \\
O^G_{j,t+1} &= O^G_{jt} + N^G_{jt} - E^G_{jt}, \\
O^B_{j,t+1} &= O^B_{jt} + N^B_{jt} - E^B_{jt},
\end{aligned}
$$

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

Acquisition quota ($Q_{j,t+1}$) is a function of the amount of outstanding loans in period $t+1$ ($O_{j,t+1}$), acquisition quota in period t (Q_{jt}) and the unobserved market condition in period $t+1$, but the exact formula is not known to us. Thus, we infer the relationship between the explanatory variables and the acquisition quota in period $t+1$, using a reduced form estimation parameterized by ϕ:

$$
Q_{j,t+1} = h(O_{j,t+1}, Q_{jt}, z_{t+1}; \phi) + \nu_{j,t+1} \tag{3}
$$

where z_t represents period fixed effects.

4.7. Utility function

A salesperson's flow utility is determined by her expected bonus and cost of effort. Salesperson j earns bonus $B(N_{jt}, R_{jt})$ based on acquisition and maintenance performance, where $N_{jt} = N_{jt}^G + N_{jt}^B$ and $R_{jt} = R_{jt}^G + R_{jt}^B$ and incurs cost $C(e_{jt})$, where $e_{jt} = \{e_{jt}^{A_G}, e_{jt}^{A_B}, e_{jt}^{M_G}, e_{jt}^{M_B}\}$. The utility function for period t is denoted as

$$U(e_{jt}, N_{jt}, R_{jt}; \Gamma, \Theta_j) = E\left[B(N_{jt}, R_{jt}; \Gamma)\right] - C(e_{jt}; \Theta_j), \tag{4}$$

where . The bonus is computed following the firm's compensation plan as $B(N_{jt}, R_{jt}; \Gamma) = \left(\frac{N_{jt}}{Q_{jt}}\right) * g\left(\frac{R_{jt}}{O_{jt}}; \gamma\right)$. Disutility comes from the cost of effort, defined as equation 5 in our empirical specification.

$$C(e_{jt}; \Theta_j) = \theta_j^C \Big[\underbrace{(e_{jt}^{A_G} + \theta_j^{A_B} e_{jt}^{A_B})}_{\text{Acquisition cost}} + \theta_j^M \underbrace{(e_{jt}^{M_G} + \theta_j^{M_B} e_{jt}^{M_B})}_{\text{Maintenance cost}}\Big]^2 \tag{5}$$

where θ_j^C is the cost parameter for total effort, $\theta_j^{A_B}$ is the cost parameter for acquiring bad loans relative to good loans, θ_j^M is the cost parameter of maintenance effort relative to acquisition effort, $\theta_j^{M_B}$ is the cost parameter for maintaining bad loans relative to good loans, and $\Theta_j = \{\theta_j^C, \theta_j^{A_B}, \theta_j^M, \theta_j^{M_B}\}$ is a vector of structural parameters. If θ_j^M is estimated to be greater than 1, monitoring task is more costly than acquisition task for salesperson j. We will distinguish a salesperson's type (e.g., which task is more comfortable to j) based on θ_j^M being greater than 1 or not. Effort cost is convex in total effort.

4.8. Bellman Equation

A salesperson makes effort decisions in a dynamically optimal manner, because acquiring more bad loans in period t can save her acquisition cost in period t, but is likely to hurt her future maintenance compensation.In other words, the effort decisions $(e_{jt}^A, e_{jt}^M, e_{jt}^{A_G}, e_{jt}^{A_B}, e_{jt}^{M_G}, e_{jt}^{M_B})$ are chosen to maximize the discounted stream of expected utility, conditional on state variables S_{jt}; compensation parameters Γ; state transition parameters ϕ; policy function parameters β_{jt} and λ_{jt}; j's belief on the probability of a loan being a good loan without private information p_{jt}^G; and the salesperson's per-period utility function that depends on structural parameters Θ. We represent the optimization problem as a value function:

$$V(S; \Gamma, \phi, \beta, \lambda, p^G, \Theta) = max_e \Big[U(e, S; p^G, \Theta) + \delta E\Big[V(S'; \Gamma, \phi, \beta, \lambda, p^G, \Theta)\Big]\Big] \tag{6}$$

where δ is a discount factor, and S' is the state variables in the subsequent periods. The expectation is taken with respect to the idiosyncratic shocks in each period.

5. Estimation

We estimate the model using a two-step estimation method (Bajari et al. 2007). The first stage is to estimate the policy functions with flexible mapping between states, actions and performance outcomes (β and λ) given the assumption that observed actions are optimally chosen by agents. The second stage is to estimate the structural parameters (Θ) using the moment inequalities approach. The moment inequalities are based on revealed preference, which we construct by comparing the payoff from the *optimal* effort functions estimated from the first stage with one from *deviated* effort functions.[11]

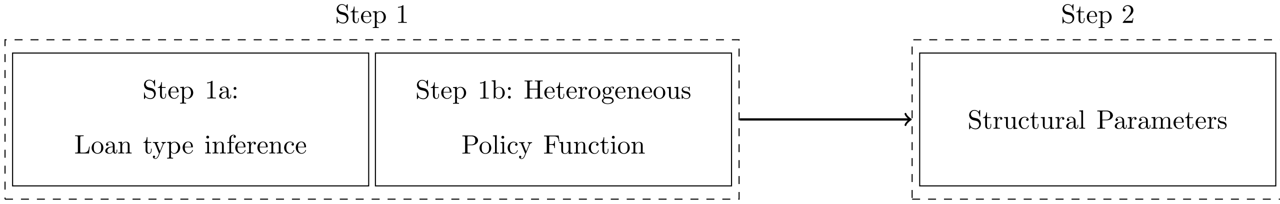
We allow salespeople to be heterogeneous in their cost of customer acquisition and maintenance.[12] The heterogeneity is essential to compare salesperson performance under multi-tasking vs. specialization, which we examine in the counterfactual simulations. The two-step approach is thus modified to accommodate unobserved salesperson heterogeneity using the EM-type algorithm in Arcidiacono and Miller (2011) and Chung et al. (2013). We estimate the heterogeneous policy functions and obtain each salesperson's probability of belonging to one of the discrete segments in the first step. We then estimate the structural parameters in the second stage by segment.

Before describing each step in detail, let us explain the challenges that need to be addressed. First, the multi-tasking salesperson makes four effort decisions given a larger number of state variables relative to single-tasking salespeople. We need to estimate flexible mappings between states and actions in the first step, but it is not straightforward to determine their functional form *a priori* due to a large number of state variables. Although semiparametric or nonparametric estimation may be an alternative way to relax the functional form assumption, it typically faces a severe curse-of-dimensionality problem. Thus, we use a machine learning method that provides us with the opportunity of high-dimensional nonparametric estimation with a careful consideration on the over-fitting problem. In particular, we utilize Random Forest to estimate the first-stage policy functions, and use cross-sample fitting to avoid over-fitting, motivated by Angrist and Krueger

[11] The two-step method is known for computational efficiency compared to the Nested Fixed Point Algorithm (Rust 1987) that solves dynamic programming problem for every value of state variables in each iteration. Computational efficiency is critical in our estimation since agents in our model simultaneously decide four actions in a dynamically optimal manner. The state space would get tremendously large depending on the combination of agent actions if we use the Nested Fixed Point Algorithm.

[12] Given that effort is unobserved, the salesforce compensation literature (e.g., Misra and Nair 2011, Chung et al. 2013) normalizes the returns to effort in terms of its effect on outcomes (sales, repayments etc.) for identification, and only estimates the cost of effort. We follow this literature, but given two dimensional effort and outcomes, estimate the cost of acquiring new loans and repayment.

Figure 4 Estimation Overview



(1995), Newey and Robins (2018) and recently applied in Belloni et al. (2012) for LASSO estimation and Athey and Imbens (2016) for tree-based estimation.

Second, a salesperson with private information makes separate effort decisions for *ex ante* good loans and bad loans. However, the loan type is not directly observed to researchers. Hence, we need to infer the loan type (*ex ante* profitability) based on observed *ex post* realized profitability. We will explain how we make inference on loan type in step 1a below, following the policy function estimation as step 1b of the first stage. Figure 4 provides the overview of our estimation procedure.

5.1. Step 1a: Loan Type Inference

A salesperson with private information in our model (e.g., continuing salesperson) makes acquisition and maintenance decisions based on loan type information. An empirical challenge is that we observe *ex post* loan profitability (e.g., realized Internal Rate of Return (IRR)) in the data, but not loan type (i.e., *ex ante* loan profitability). The *ex ante* profitability is different from the observed *ex post* profitability because a salesperson can affect loan profitability during a loan cycle. Thus, we infer the *ex ante* profitability based on the observed *ex post* profitability, controlling for 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).

5.1.1. Mapping between observables and loan profitability To do so, we first fit Internal Rate of Return of loan i (IRR_i), which represents *ex post* loan profitability, using random forest:

$$IRR_i = f(L_i, S_{j(i)}, State_{j(i)t \ldots T(i)}) + u_i \tag{7}$$

where the explanatory variables include loan/borrower characteristics of loan i (L_i), segment of salesperson j who acquires loan i ($S_{j(i)}$) and salesperson characteristics and compensation states aggregated during the loan cycle, from the acquisition period t to the

Table 3 Variables used to Develop a Predictive Model

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

maturity T ($S_{j(i)t...T(i)}$)). Table 3 summarizes the explanatory variables observed in the data. Here, L_i includes loan characteristics (e.g., period, requested loan amount, whether the loan is a group loan, the number of signers to guarantee the borrower's credibility, whether the loan was renewed, purpose of loans, borrower's self-reported number/amount of cumulative loans, borrower credit rating, gender, whether a borrower owns a property and borrower's occupation) and loan terms (e.g., interest rate, duration and amount). Salesperson characteristics (e.g., level, tenure, branch that a salesperson works for, the number of new loans through automatic process or visitors) and compensation states (e.g., acquisition quota, acquisition index at time of acquisition and average maintenance index during a loan cycle) are denoted as $S_{j(i)t...T(i)}$. Salesperson segment ($S_{j(i)}$) is not observed in the data, and we will come back to this point to explain how we control for $S_{j(i)}$.

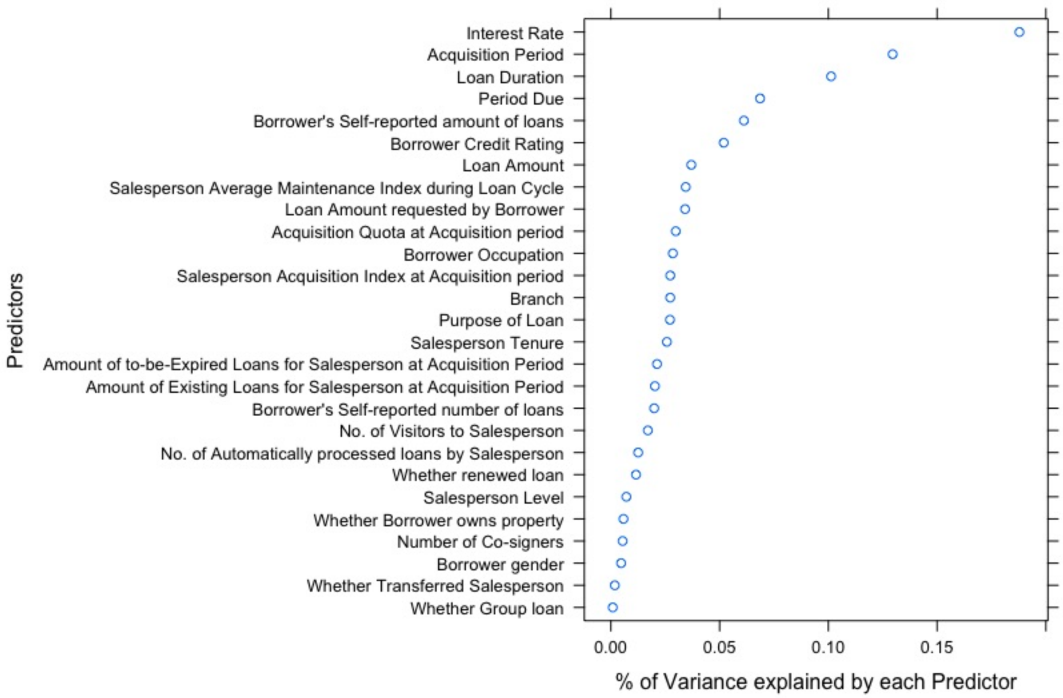
Random Forest method is not only easy and fast to implement, but also produces very accurate out-of-sample fits, especially with highly nonlinear models (Howard and Bowles 2012, Caruana and Niculescu-Mizil 2006) for the following reasons.[13] First, the method allows us not to make any assumption about which variables are considered important to salespeople. The data contains 26 variables on loan characteristics and salesperson characteristics/compensation states summarized in Table 3, thus it is hard to make a sufficiently flexible specification that incorporates all the explanatory variables that might affect a salesperson's actions. Varian (2014) evaluates the method very favorably for use in economics research, since Random Forest can determine which variables are important in predictions, in terms of the contribution to improve prediction accuracy, although a forest with thousands of trees is not easy to interpret by itself. Further, the computer science literature (Breiman 2001) shows that Random Forest overcomes accuracy problems with decision trees, due to over-fitting of the training data, and a resulting risk of high out-of-sample predictive variance.

The data for the estimation of $f(.)$ contains 60,970 loans where we can observe the full set of predictors, out of 100,250 loans. The algorithm constructs multiple decision trees to train the data, and verifies the fit through cross-validation to find the optimal number of trees, and the optimal number of variables used to grow each tree. We find that 1,000 trees with 15 predictors gives the best prediction with the lowest mean square error for the test data. The top panel of Figure 5.1.3 shows the importance of each variable in classifying the loans. Variable importance represents the normalized percentage of variance explained by each variable.

5.1.2. Control for Salesperson factors To predict ex ante profitability, we control for salesperson factors, such as salesperson segment $S_{j(i)}$ (e.g., if salesperson j who acquires loan i is more efficient at acquisition or maintenance) and characteristics/states $State_{j(i)t...T(i)}$ (e.g., how many loans are to be collected by j on average from period t to

[13] Kumar et al. (2016) verifies the high prediction accuracy of the method in the context of loan repayment.

Figure 5 Variable Importance



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 *ex post* IRR of loan i.[14] We compute the *ex ante* IRR ($I\hat{R}R_i$):

$$I\hat{R}R_i = \hat{f}(L_i, \tilde{S}_{j(i)}, St\tilde{a}te_{j(i)}).$$

where $\tilde{S}_{j(i)}$ is the fixed effect for salesperson segment and $St\tilde{a}te_{j(i)t...T(i)}$ is the average compensation states of salesperson j across all loans/periods.[15] We need to handle two empirical challenges in computing ex ante IRR: unobservability of $S_{j(i)}$ and endogeneity of $State_{j(i)t...T(i)}$.

First, salesperson segment $S_{j(i)}$ is not directly observed in the data. It is also hard to control with salesperson fixed effects, because there are not enough data points of each

[14] A segment of salespeople who are more efficient at the maintenance task would do more monitoring than the other segment. Kim et al. (2018) 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.

[15] We choose to control *State* with the average compensation states of salesperson j to take into account salesperson-specific compensation pressure. A salesperson who has low maintenance index in all periods might not feel much pressure although she can't collect many loans and earns very low maintenance index.

salesperson. Thus, we take advantage of the EM-algorithm that is used in the step 1b (heterogeneous policy function estimation) in Figure 4. From step 1b, which is elaborated in the next subsection, we obtain the probability of each salesperson belonging to each segment, which gives us information on if each salesperson is more efficient at acquisition or maintenance. We start from step 1a, assuming the equal share of each segment of salespeople, to obtain loan types, and use the inferred private information to estimate each salesperson's segment and heterogeneous policy functions in step 1b. Then we come back to step 1a to take advantage of the estimated salesperson segment and infer loan types again. The iterative procedure between step 1a and step 1b within the step 1 would enable us to jointly estimate loan type and salesperson segment, and to control for salesperson segment $S_{j(i)}$ in the loan type inference.

Next, salesperson characteristics and time-varying compensation states $State_{j(i)t...T(i)}$ are observed in the data. However, an unobserved factor (e.g., loan type) can affect both $State_{j(i)t...T(i)}$ and IRR_i in equation (7), thus merely controlling for the states would not be sufficient to infer *ex ante* loan profitability. To handle the endogeneity, we instrument $State_{j(i)t...T(i)}$ with $Z_{j(i)t...T(i)}$, which affects salesperson compensation states ($State_{j(i)t...T(i)}$), but does not affect the return of loan i (IRR_i). The instrument $Z_{j(i)t...T(i)}$ includes (i) salesperson j's transfer status, (ii) average IRR of the other loans acquired by salesperson j in period t, and (iii) average IRR of the other loans maintained by salesperson j in period t. Such variables affect $State_{j(i)t...T(i)}$ because salesperson compensation states are determined by the *aggregate* profitability of loans in j's portfolio, but does not directly affect IRR_i, which is solely determined by loan i's profitability.

We use Deep IV (Hartford et al. 2017) for the instrumental variable approach. The Deep IV algorithm flexibly takes care of endogeneity by incorporating machine learning techniques in IV estimation. The detailed procedure is provided in the appendix.

5.1.3. Classification of Loans 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 excluded loans and included loans, in terms of the value of loan characteristics and salesperson characteristics/states. The similarity of predictors is weighted by the variable importance in Figure to obtain propensity score. We plug in $\hat{IRR}_{ijt}$ of a matched loan to each of 39,280 loans.

Then, loan i is classified into a good loan (i.e. a profitable, but harder-to-acquire loan) if $I\hat{R}R_i$ is greater than the minimum interest rate of all loans, which represents the minimum return that the firm wants to achieve from fully-repaid loans, and a bad loan (i.e. a unprofitable, but easier-to-acquire loan) otherwise. We find good loans account for 67% of the loans in the data.

Since our model investigates each salesperson's acquisition/maintenance decisions, instead of each loan's behaviors, we aggregate the loan-level type information to obtain the amount of acquired or repaid loans by loan type, for each salesperson in each period. In other words, four new variables are created from the predictive model: the amount of new good loans (N_{jt}^G), that of new bad loans (N_{jt}^B), that of repaid good loans (R_{jt}^G), and that of repaid bad loans (R_{jt}^B). We use the constructed variables for the two-step estimation.

5.2. Step 1b: Heterogeneous Policy Function Estimation

We estimate a salesperson's policy function for acquisition and maintenance behaviors in this step. There are two empirical challenges that we need to address. First, a multi-tasking salesperson makes simultaneous decisions on acquisition and maintenance, i.e., j with private information chooses $e_{jt}^{A_G}$, $e_{jt}^{A_B}$, $e_{jt}^{M_G}$ and $e_{jt}^{M_B}$ at the same time in period t.[16] The simultaneity leads all effort actions to be interconnected. For example, the choice of $e_{jt}^{A_G}$ depends on j's choice on $e_{jt}^{A_B}$, and vice versa, since the distribution of acquired loan types in period t shifts j's maintenance behavior in the subsequent periods. Maintenance efforts ($e_{jt}^{M_G}$ and $e_{jt}^{M_B}$) affect acquisition efforts ($e_{jt}^{A_G}$ and $e_{jt}^{A_B}$) and vice versa, because j splits limited time/resource into two tasks[17] and faces the complementarity between the two tasks. The policy function estimation is not intended to find *causality* between state variables and observed actions, but to *predict* observed actions based on state variables. The computational efficiency of the two-step estimator is due to the assumption that the actions are optimally chosen, given state variables. Considering such purpose of the policy

[16] Without private information, two actions (e_{jt}^A and e_{jt}^M) are chosen simultaneously and each effort is allocated into good and bad loans, beyond j's control.

[17] We do not explicitly model the limited total time/resource that j allocates between multiple tasks, because it's hard to assume that all salespeople spend equal amount of time at work. However, modeling that acquisition efforts and maintenance efforts affect each other handles that a salesperson faces the allocation problem.

function estimation, we choose to represent each action (modeled in equations (1) and (2)) as a function of all state variables in a reduced-form way as follows:

$$\begin{aligned}
e_{jt}^{A_G}(S_{jt}) &\equiv e_{jt}^{A_G}(s_{jt}^{A_G}, s_{jt}^{A_B}, s_{jt}^{M_G}, s_{jt}^{M_B}),\\
e_{jt}^{A_B}(S_{jt}) &\equiv e_{jt}^{A_G}(s_{jt}^{A_G}, s_{jt}^{A_B}, s_{jt}^{M_G}, s_{jt}^{M_B}),\\
e_{jt}^{M_G}(S_{jt}) &\equiv e_{jt}^{A_G}(s_{jt}^{A_G}, s_{jt}^{A_B}, s_{jt}^{M_G}, s_{jt}^{M_B}),\\
e_{jt}^{M_B}(S_{jt}) &\equiv e_{jt}^{A_G}(s_{jt}^{A_G}, s_{jt}^{A_B}, s_{jt}^{M_G}, s_{jt}^{M_B})
\end{aligned}$$

Second, salesperson actions are *unobserved* and our performance metrics result from salesperson actions and exogenous shifters. In order to efficiently distinguish the impact of each driver and estimate unknown effort functions, we assume that effort is a deterministic function of state variables following Misra and Nair (2011), Chung et al. (2013) and use a semi-parametric policy function for each performance outcome variable (modeled in equations (1) and (2)) as follows:

$$\begin{aligned}
N_{jt}^{G} &= e_{jt}^{A_G}(S_{jt}; \lambda_j^{A_G}) + f(X_{jt}; \beta_j^{A_G}) + \epsilon_{jt}^{A_G},\\
N_{jt}^{B} &= e_{jt}^{A_B}(S_{jt}; \lambda_j^{A_B}) + f(X_{jt}; \beta_j^{A_B}) + \epsilon_{jt}^{A_B},\\
R_{jt}^{G} &= e_{jt}^{M_G}(S_{jt}; \lambda_j^{M_G}) + f(X_{jt}; \beta_j^{M_G}) + \epsilon_{jt}^{M_G},\\
R_{jt}^{B} &= e_{jt}^{M_B}(S_{jt}; \lambda_j^{M_B}) + f(X_{jt}; \beta_j^{M_B}) + \epsilon_{jt}^{M_B}
\end{aligned}$$

where $e_{jt}^{A_G}$, $e_{jt}^{A_B}$, $e_{jt}^{M_G}$ and $e_{jt}^{M_B}$ are nonparametrically modeled as a function of all state variables and $f(.)$ is a linear function of exogenous shifters X_{jt}. State variable S_{jt} is the union of all the state variables described in Table 2. The exogenous shifters X_{jt} include branch-level average acquisition quota $\overline{Q}_t^b$; and the interaction between tenure τ_{jt} and $\overline{Q}_t^b$. 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. The four-dimensional shocks $(\epsilon_{jt}^{A_G}, \epsilon_{jt}^{A_B}, \epsilon_{jt}^{M_G}, \epsilon_{jt}^{M_B})$ are generated from a multivariate normal distribution with mean 0 and covariance Σ_{jt}, correlated with each other for the same salesperson in the same period, and i.i.d across salespeople or across periods. The correlation across shocks within salesperson-period comes from unanticipated shocks that affect all performance metrics of a salesperson, such as an unexpected medical condition that prevents him from reaching out to potential or existing customers.

The model enables us to focus on the separate impact of effort and exogenous shifters for each performance outcome. We make use of a machine learning approach to allow a very flexible effort function. It is important not to make a restrictive assumption on the functional form, which might lead to biased structural parameter estimates. [18] Specifically, we use random forest model due to high predictive power and flexibility for the nonparametric estimation (Mullainathan and Spiess 2017).

We use the backfitting algorithm (Buja et al. 1989) for the semiparametric estimation.[19] The key idea is to estimate the additive components separately on partial residuals. The method iteratively solves for $\hat{e}_{jt}$ and $\left(\hat{\beta}_{jt}, \hat{\Sigma}_{jt}\right)$ by replacing the conditional expectation of the partial residuals at each stage (Bickel et al. 2005) as follows.

1. Initialize $\hat{\beta}_{jt}^{A_G}$, $\hat{\beta}_{jt}^{A_B}$, $\hat{\beta}_{jt}^{M_G}$, $\hat{\beta}_{jt}^{M_B}$, $\hat{e}_{jt}^{A_G}$, $\hat{e}_{jt}^{A_B}$, $\hat{e}_{jt}^{M_G}$, $\hat{e}_{jt}^{M_B}$ and $\hat{\Sigma}_{jt}$.
2. $E\left(\begin{bmatrix} N_{jt}^G - f(X_{jt}^{A_G}; \hat{\beta}_{jt}^{A_G}) \\ N_{jt}^B - f(X_{jt}^{A_B}; \hat{\beta}_{jt}^{A_B}) \\ R_{jt}^G - f(X_{jt}^{M_G}; \hat{\beta}_{jt}^{M_G}) \\ R_{jt}^B - f(X_{jt}^{M_B}; \hat{\beta}_{jt}^{M_B}) \end{bmatrix} | S_{jt}\right) = \begin{bmatrix} \hat{e}_{jt}^{A_G}(S_{jt}) \\ \hat{e}_{jt}^{A_B}(S_{jt}) \\ \hat{e}_{jt}^{M_G}(S_{jt}) \\ \hat{e}_{jt}^{M_B}(S_{jt}) \end{bmatrix}$
3. $(\hat{\beta}_{jt}^{A_G}, \hat{\beta}_{jt}^{A_B}, \hat{\beta}_{jt}^{M_G}, \hat{\beta}_{jt}^{M_B}, \hat{\Sigma}_{jt}) = \arg\max L_j\left(\begin{bmatrix} N_{jt}^G - \hat{e}_{jt}^{A_G}(S_{jt}) \\ N_{jt}^B - \hat{e}_{jt}^{A_B}(S_{jt}) \\ R_{jt}^G - \hat{e}_{jt}^{M_G}(S_{jt}) \\ R_{jt}^B - \hat{e}_{jt}^{M_B}(S_{jt}) \end{bmatrix}\right)$
4. Iterate $2-3$ until convergence.

where the step 3 maximizes the full information likelihood of four residuals $(\epsilon_{jt}^{A_G}, \epsilon_{jt}^{A_B}, \epsilon_{jt}^{M_G}, \epsilon_{jt}^{M_B})$, which follow the multivariate normal distribution with mean 0 and covariance Σ_{jt}.

We combine the algorithm with cross-sample fitting to eliminate overfitting and ensure the consistency of the estimator under a very high-dimensional effort function (Chernozhukov et al. 2018), motivated by Newey and Powell (2003). The idea is that we randomly divide all data points into the main and auxiliary samples, each of which takes up 50% of the data, obtain the estimates ($\hat{\beta}_{jt}^{A_G}$, $\hat{\beta}_{jt}^{A_B}$, $\hat{\beta}_{jt}^{M_G}$, $\hat{\beta}_{jt}^{M_B}$, $\hat{\gamma}_{jt}^{A_G}$, $\hat{\gamma}_{jt}^{A_B}$, $\hat{\gamma}_{jt}^{M_G}$, $\hat{\gamma}_{jt}^{M_B}$ and $\hat{\Sigma}_{jt}$) from the main sample only and those from the auxiliary sample only, and then average the results across samples.

In addition, to answer our research questions, it is critical to accommodate unobserved heterogeneity across salespeople and find which salesperson is more comfortable with the acquisition or maintenance task, because heterogeneous cost of effort across salespeople

[18] Igami (2017) suggests use of machine learning approaches for policy function estimation to ensure the flexibility.

[19] The consistency of the backfitting estimators are examined based on local polynomial regression (Opsomer and Ruppert 1997) and most kernel regressions (Mammen et al. 1999).

determines the profitability of counterfactual job/incentive designs (e.g., specialization). Since lack of data points for each salesperson does not enable us to observe utility functions at the individual salesperson level, we incorporate persistent unobserved heterogeneity across salespeople at the discrete segment level. We apply the Expectation-Maximization (EM) Algorithm developed in Arcidiacono and Jones (2003) and Arcidiacono and Miller (2011) and empirically applied in Chung et al. (2013).

We are interested in estimating segment-level effort $e_k^{A_G}, e_k^{A_B}, e_k^{M_G}, e_k^{M_B}$ and covariance Σ_k (where segment $k = 1, 2, ..., K$ and K is the number of discrete segments), instead of individual salesperson-level effort $e_j^{A_G}, e_j^{A_B}, e_j^{M_G}, e_j^{M_B}$ and covariance Σ_j. Following the application in Chung et al. (2013), we compute L_{jkt}, the full information likelihood of simultaneously observing salesperson j's acquisition and maintenance performance $(N_{jt}^G, N_{jt}^B, R_{jt}^G, R_{jt}^B)$ given segment-level parameters and the persistent segment k that salesperson j belongs to:

$$L_{jkt} = L(N_{jt}^G, N_{jt}^B, R_{jt}^G, R_{jt}^B | k; e_k, \beta_k, \Sigma_k)$$

Next, we estimate the parameters by maximizing the full information likelihood, weighted by the probability of salesperson j being in segment k (q_{jk}):

$$\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} q_{jk} L_{jkt} \tag{8}$$

where

$$q_{jk} = Pr(k | N_{jt}^G, N_{jt}^B, R_{jt}^G, R_{jt}^B; e, \beta, \Sigma, p) = \frac{p_k \big(\prod_{t=1}^{T} L_{jkt} \big)}{\sum_{k=1}^{K} p_k \big(\prod_{t=1}^{T} L_{jkt} \big)} \tag{9}$$

and p_k is the size of segment k. The innovation of the approach in Arcidiacono and Miller (2011) is that we do not need to maximize the log-likelihood of the likelihood of observing salesperson j's performance given all of the possible combinations of latent segments that each salesperson can belong to.[20] The iterative process is as follows for the $(m+1)^{th}$ iteration:

1. Compute $q_{jk}^{(m+1)}$ using equation 9 with $e^{(m)}, \beta^{(m)}, \Sigma^{(m)}$ and $p^{(m)}$.
2. Obtain $e^{(m+1)}, \beta^{(m+1)}$ and $\Sigma^{(m+1)}$ by full information maximum likelihood, weighted by $q_{jk}^{(m+1)}$ in equation 8.
3. Update $p^{(m+1)}$ by taking the average of $q_{jk}^{(m+1)}$.

[20] Details are described in Chung et al. (2013). The main point is that the sum of log-likelihood of observing salesperson j's performance, over all of the unobserved states $\sum_j^J logL((N_{jt}^G, N_{jt}^B, R_{jt}^G, R_{jt}^B; e, \beta, \Sigma, p))$ is not additively separable.

We iterate $1-3$ till convergence. The initial values are estimates of e, β and Σ without unobserved heterogeneity, and random size p that sums up to 1.

As discussed above, after finding which segment each salesperson belongs to, we go back to the step 1a (loan type inference) to use the information on salesperson segment to infer the *ex ante* loan profitability. We iterate between the step 1a and the step 1b twice and find the estimates converge.

5.2.1. Step 2: Structural Parameter Estimation The second stage of the estimation method aims to estimate structural parameters Θ_k, consisting of the cost related to the total effort (θ_k); the cost of acquisition effort for bad loans relative to good loans ($\theta_k^{A_B}$); the cost of maintenance effort relative to acquisition effort (θ_k^M) and the cost of maintenance effort for bad loans relative to good loans ($\theta_k^{M_B}$). This step relies on the assumption that our policy function estimates reveal the mapping between state variables and *optimal* actions of agents. Thus, using the policy function estimates and state transition estimates, we can recover the value function that a salesperson attempts to maximize by behaving optimally. The forward-simulation process to estimate the value function from *optimal* policy estimates are as follows:

1. Start from initial values of state variables S_{j0}.
2. A random number α_{jt} is drawn from $U[0,1]$. If α_{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 $e_{kt}(S_{jt}; \gamma_k)$. Compute the impact of exogenous shifters using estimated β_k at the first stage as $f(X_{jt}; \beta_k)$
4. Unanticipated shocks for each performance ϵ_{jt} are drawn from a multivariate normal distribution of mean zero and estimated covariance Σ_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. The transfer probability is set to 0.04, 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 Θ_k: $\hat{V}(S|k; e_k, \beta_k, \Sigma_k, \phi, \Theta_k)$. Next, we do the same forward-simulation with *deviated* policy rule from the estimated effort function. The deviated effort policy parameters are denoted as $\tilde{e}_k$. Then, we estimate the value function from deviated actions for each segment given structural parameters: $\tilde{V}(s|k;\tilde{e}_k,\beta_k,\Sigma_k,\phi,\Theta_k)$. The value function from deviated actions is no greater than the one from optimal actions by definition.

We estimate segment-level structural parameters as the minimum distance estimator of the difference between $\tilde{V}(s|k;\tilde{e}_k,\beta_k,\Sigma_k,\phi,\Theta_k)$ and $\hat{V}(s|k;e_k,\beta_k,\Sigma_k,\phi,\Theta_k)$ for each segment:

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

5.3. Identification

As discussed above, our rich data on loan-level transactions allows us to identify (i) multi-tasking and (ii) private information. The detailed data separately shows revenue from new loans (as a result of salesperson acquisition behavior) and that from existing loans (as a result of salesperson maintenance behavior) for the estimation of multi-tasking. For the estimation of effort allocation based on private information, each loan's repayment history enables us to observe ex post profitability of each loan, and to separately infer revenue from ex ante good loans and that from ex ante bad loans. Specifically, we observe four performance outcomes (N_{jt}^G,N_{jt}^B,R_{jt}^G and R_{jt}^B) that correspond to each effort decision ($e_{jt}^{A_G}$,$e_{jt}^{A_B}$,$e_{jt}^{M_G}$ and $e_{jt}^{M_B}$), which does not require us to make any additional assumptions relative to Misra and Nair (2011) and Chung et al. (2013) for estimating the uni-dimensional effort function.

Next, we need to separately identify the effect of private information and cost of effort in decisions. First, the transfer policy allows us to have variation in private information *within* salesperson. We assume continuing salespeople have private information and make *four* effort decisions, whereas transferred salespeople do not have private information and make *two* effort decisions. Next, the difference in acquisition/maintenance behaviors across continuing salespeople is attributed to the difference in cost of effort. Although transferred salespeople make only two decisions, we can identify their cost of effort for different types of loans as well, since transferred salespeople's decisions are allocated into good and bad loans beyond the salespeople's control.

6. Results

In this section, we report the transition parameters of acquisition quota; policy function parameters from the first step; structural parameters from the second step; and the counterfactual simulation results to investigate which job/incentive design makes the firm better off.

6.1. State Transition

The acquisition quota of a continuing salesperson is known to increase in the volume of her existing loans, with the base levels varying across periods. The policy serves as a limit to a continuing sales agent's acquisition effort, since the quota depends on her cumulative action up to the period. Although the exact quota-setting rule is not observed, we attempt to recover the policy using observed data. The following transition function is examined, to estimate the relationship between the amount of outstanding loans, the lagged quota and the current quota.

$$Q_{j,t+1} = \sum_{l=0}^{3} \kappa_l \Lambda_l(O_{j,t+1}) \Lambda_l(Q_{jt}) + \mu_{t+1} + \varepsilon_{j,t+1} \tag{10}$$

where $\Lambda_l(.)$ represents the l^{th} basis of the 3^{rd} order Chebyshev polynomial, parameterized by κ_l. Period fixed effect μ_{t+1} is considered to capture the variability of quota depending on the market condition. The shock $\varepsilon_{j,t+1}$ is not observed before the beginning of period $t+1$. The specifications in Table 4 support the positive impact of the predictors $(O_{j,t+1}, Q_{jt})$ on the acquisition quota, to verify the ratcheting policy on continuing salespeople.

Table 4 Transition of Acquisition Quota: Ratcheting Policy

	DV: $Q_{j,t+1}$			
	Continuing		Transferred	
	(1)	(2)	(1)	(2)
$\Lambda_1(O_{j,t+1})$	1.00***	0.49***	1.29*	0.79
	(0.01)	(0.12)	(0.75)	(0.94)
$\Lambda_2(O_{j,t+1})$	-0.001***	-1.30e-04	-0.002	-0.0009
	(0.0003)	(0.0003)	-0.003	(0.003)
$\Lambda_3(O_{j,t+1})$	6.9e-07***	-4.9e-08	-1.7e-06	5.02e-07
	(2.3e-07)	(2.3e-07)	(2.4e-06)	(2.7e-06)
$\Lambda_1(Q_{jt})$	-1.18***	-0.37***	-0.72	-0.10
	(0.1)	(0.11)	(0.62)	(0.69)
$\Lambda_2(Q_{jt})$	0.004***	0.001***	0.002	0.0007
	(0.0003)	(0.0003)	(0.002)	(0.002)
$\Lambda_3(Q_{jt})$	-2.3e-06***	-7.0e-07***	1.6e-06	-9.9e-07
	(2.7e-07)	(2.6e-07)	(1.5e-06)	(1.6e-06)
$\Lambda_2(O_{j,t+1}) * \Lambda_2(Q_{jt})$	-2.0e-09***	-1.6e-09***	-1.60e-10	3.80e-10
	(3.4e-10)	(3.1e-10)	(2.6e-09)	(2.7e-09)
Period FE	No	Yes	No	Yes
Intercept	16.68***	17.68**	26.71	91.54
	(4.8)	(8.37)	(25.73)	(55.83)
N	2276	2276	154	154
R^2	0.28	0.45	0.23	0.31

The ratcheting incentive is defined as the use of current performance as a basis for future quota (i.e., target). The amount of outstanding loans represents the cumulative acquisition performance up to period t, although it might not be directly related to N_{jt}. Acquisition quota in period t Q_{jt} captures cumulative effort up to period $t-1$, and at the same time, disciplines acquisition performance in period t N_{jt}. In other words, N_{jt} is implicitly a basis for $Q_{j,t+1}$. Thus, a salesperson needs to anticipate how much the quota would be in the future periods when choosing acquisition effort.

However, the ratcheting policy does not apply to a transferred salesperson. For a transferred salesperson $O_{j,t+1}$ represents the amount of outstanding loans, which were acquired by the predecessor and j faces at the beginning of $t+1$, and Q_{jt} denotes the j's own quota in period t. Insignificant impacts of $O_{j,t+1}$ and Q_{jt} in Model 4 imply that quota is basically reset for a transferred salesperson, independent of her own performance or predecessor's performance in the previous period. Model 3 shows that the acquisition quota is positively correlated with $O_{j,t+1}$ at the marginally significance level, but still $O_{j,t+1}$ is beyond what j can control for. The firm claimed the transferred salesperson's quota is based on the branch-level market condition (e.g., average quota of the loan officers in the new branch). Then, the acquisition quota after transfer would not be systematically higher or lower than the quota before transfer, since the timing and location of transfer is randomly determined. Although branch/period fixed effects could not fully explain the new quota for a transferred salesperson according to our analysis, we at least verify that the quota transition does not follow the ratcheting policy.

6.2. Policy Function Estimates

We report the estimates of β_k by segment in Table 5a. Standard deviations in the parentheses are to be added. The first two panels shows the impact of exogenous shifters on the acquisition performance for good loans and that for bad loans, respectively. As the market condition gets better, acquisition performances go up. The market effect on good loan acquisition is attenuated for experienced salespeople, and that on bad loan acquisition is strengthened as a salesperson works for the firm for longer time. We conjecture that salespeople with longer tenure take advantage of good market condition to engage in adverse customer selection. The bottom two panels represent the change in maintenance performance for good and bad loans depending on branch-level market conditions. As the branch-level average quota goes up, salespeople choose to focus on acquiring new customers, relative to maintaining existing customers. Our estimates imply that sales agents in a good market condition selectively maintain existing loans that are likely to respond to monitoring (i.e., good loans). The patterns is more salient for experienced salespeople. We find similar β_k for the two segments, because the impact of market condition is beyond the agent's decision, although salespeople might be heterogeneous in terms of ability in each task. Each segment accounts for 68% and 32% of the salespeople.

Table 5a Policy Function Estimates

	Segment 1	Segment 2
β^{A_G}		
Average Quota (branch)	44.68	38.15
Tenure * Average Quota (branch)	-10.44	-9.27
Intercept	-6.81	-6.92
β^{A_B}		
Average Quota (branch)	11.94	9.38
Tenure * Average Quota (branch)	4.32	4.91
Intercept	-8.55	-6.22
β^{M_G}		
Average Quota (branch)	-1.28	-0.45
Tenure * Average Quota (branch)	1.44	1.17
Intercept	-1.78	-1.57
β^{M_B}		
Average Quota (branch)	-33.04	-33.21
Tenure * Average Quota (branch)	0.92	0.95
Intercept	3.07	3.07
Share	68 %	32 %

Table 5b shows the estimated covariance of shocks (Σ_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 ($\epsilon_k^{A_G}$ and $\epsilon_k^{A_B}$) 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 $\epsilon_k^{M_G}$ and $\epsilon_k^{M_B}$).

Table 5b **Distribution of Multidimensional Shocks**

	Segment 1	Segment 2
$Var(\epsilon^{A_G})$	241.54	235.28
$Var(\epsilon^{A_B})$	329.71	326.63
$Var(\epsilon^{M_G})$	15.58	15.59
$Var(\epsilon^{M_B})$	39.79	232.66
$Cov(\epsilon^{A_G}, \epsilon^{A_B})$	-116.09	-119.03
$Cov(\epsilon^{A_G}, \epsilon^{M_G})$	-0.81	-0.11
$Cov(\epsilon^{A_G}, \epsilon^{M_B})$	4.11	4.11
$Cov(\epsilon^{A_B}, \epsilon^{M_G})$	-0.99	-0.7
$Cov(\epsilon^{A_B}, \epsilon^{M_B})$	16.89	-15.32
$Cov(\epsilon^{M_G}, \epsilon^{M_B})$	0.34	2.59

6.3. Structural Parameter Estimates

In the second step, we estimate four structural parameters that govern a salesperson's cost ($\theta_k^C, \theta_k^{A_B}, \theta_k^M, \theta_k^{M_B}$) reported in Table 6. Segment 1, which takes up 68% of the salespeople, incurs lower effort cost (i.e., more skilled and efficient) than segment 2, which accounts for 32%. Based on $\theta_k^{A_B}$, bad customers are much easier to acquire for segment 1, whereas good and bad customers are not very distinguishable in terms of acquisition cost to segment 2. Most importantly, based on θ_k^M, the maintenance task accounts for slightly larger portion of effort cost to segment 1, whereas the acquisition task is more costly to salespeople belonging to segment 2. We call segment 1 as the "hunter" segment relatively good at acquiring new customers, and segment 2 as the "farmer" segment who has a comparative advantage in collecting past loans. To interpret the estimates of $\theta_k^{M_B}$, the two types are not very different in terms of maintenance cost to segment 1, but a bad loan is much harder to maintain for segment 2. In other words, the "hunter" segment who notice that bad loans are much lower-hanging fruits to acquire (i.e., low $\theta_k^{A_B}$), acquisition task is no harder than maintenance task (i.e., high θ_k^M) and total effort is not very costly (i.e., low θ_k^C). Maintenance task is burdensome, however, because collecting good loans and bad loans are not very distinguishable in terms of cost (i.e., low $\theta_k^{M_B}$). They do not have merits in getting repayments from good loans compared to bad loans. Next, we find that salesperson effort cost is largely explained by acquisition cost (i.e., low θ_k^M) to salespeople in the "farmer" segment, who judge that even bad loans are not easy to acquire (i.e., high $\theta_k^{A_B}$). Maintenance task incurs them smaller cost because they can easily collect good loans compared to bad loans (i.e., high $\theta_k^{M_B}$). They are more likely to be low-skilled salespeople (i.e., high θ_k).

Table 6 Structural Parameters

	Segment 1 (Hunter)	Segment 2 (Farmer)
Total Cost (θ_k^C)	1.970	3.292
Relative Acquisition Cost of Bad Loans ($\theta_k^{A_B}$)	0.146	0.966
Relative Cost of Maintenance Effort (θ_k^M)	1.062	0.306
Relative Maintenance Cost of Bad Loans ($\theta_k^{M_B}$)	0.960	2.956
Share	68 %	32 %

where $C(e_{jt};\Theta_j) = \theta_j^C\left[(e_{jt}^{A_G} + \theta_j^{A_B} e_{jt}^{A_B}) + \theta_j^M(e_{jt}^{M_G} + \theta_j^{M_B} e_{jt}^{M_B})\right]^2$.

6.4. Counterfactual Simulation

Based on the estimated structural parameters, we simulate counterfactual policies around (i) job design, (ii) incentive design, and (iii) transfer policy to eliminate private information. The first simulation examines the role of multi-tasking. Our structural parameter estimates show that salespeople are heterogeneous in terms of which task they are more efficient at. The "hunter" segment is good at bringing in new sales relative to maintaining the relationship with previously acquired customers. Salespeople in the "farmer" segment are better at collecting repayment from existing customers than acquiring new customers, implied by their lower maintenance effort cost than their acquisition cost. Thus, a natural question is if the firm benefits from assigning each salesperson a task that is *less arduous*.[21] The multi-tasking can lead to better incentive alignment between salespeople and the firm, but less efficient outcome by forcing all salespeople to work on all tasks. Our counterfactual simulation quantifies the net effect of the multi-tasking job/multi-dimensional incentives compared to single-tasking/uni-dimensional incentives and presents a mechanism.

The second simulation studies the role of complementarity imposed by the incentive scheme. MacDonald and Marx (2001) theoretically shows that the additive incentive scheme (e.g., $Bonus = A + M$) induces salespeople to gravitate towards what they are more efficient at, when the two tasks considered as substitutes by salespeople (in terms of time, resource and effort) under the additive plan. Such induced *specialization* is detrimental to the firm's profit when the firm considers the two tasks as complementary, thus they call it "adverse specialization". MacDonald and Marx (2001) suggest that the firm need to induce complementarity between the two tasks by using a multiplicative incentive scheme. However, in our setting, the two tasks are already complementary from the

[21] Godes (2004) provides the condition that division of labor is preferred to multi-tasking.

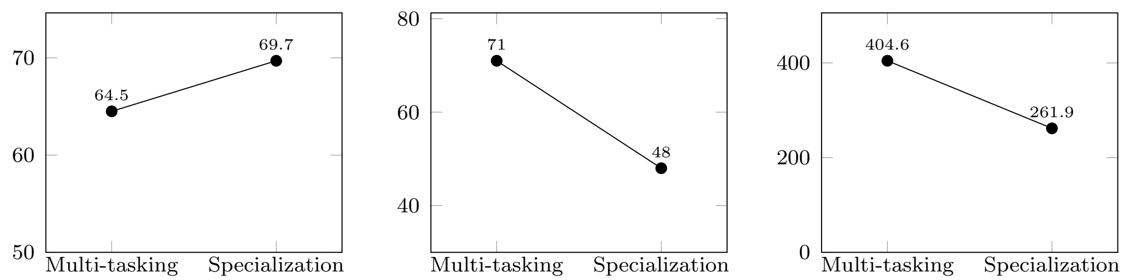
salespeople's standpoint. A salesperson can maintain a loan only when she acquired it in the previous period. It is now an empirical question whether the additive incentive scheme is sufficient to induce salespeople to balance effort between the two tasks, or the firm should strengthen the complementarity using multiplicative incentive scheme, when complementarity is already built in the nature of the tasks. We quantify the effect of enhanced complementarity on the behaviors of each segment of salespeople under the additive and multiplicative incentive scheme.

The third simulation examines the role of private information on salesperson performance and profitability. Private information is a double-edged sword: it can help salespeople acquire less risky loans and make better maintenance decisions (i.e., increase efficiency) but leads to salesperson moral hazard to acquire less profitable, but easier-to-acquire customers (i.e., create incentive misalignment). The firm randomly transfers salespeople between branches to eliminate salesperson private information. If the cost of private information due to incentive misalignment outweighs the benefit of private information from efficiency gain, the firm would be better off with the transfer policy that prevents salesperson moral hazard. We quantify the net effect of the transfer policy and suggest how to improve the policy for the firm to benefit from private information.

The counterfactual policies are tested for 500 paths on a hypothetical salesperson from each segment. With private information, the agent is able to observe loan types and choose acquisition and maintenance efforts by type. Without private information, good and bad loans are not differentiated and the decision variables are acquisition and maintenance efforts, regardless of type. We use the policy function iteration using the estimated structural parameters to obtain the Net Present Value of acquired loans, and revenue from each task and each type of loans.

6.4.1. Job Design The first simulation compares salesperson performance and profitability under multi-tasking (all salespeople responsible for acquisition and maintenance), and specialization (acquisition task assigned to "hunters"; maintenance task assigned to "farmers"). Table 7 reports acquisition/maintenance performance on each type of loans and Net Present Value (NPV) under multi-tasking and specialization. Under multi-tasking, all salespeople are incentivized based on multi-dimensional performances ($Bonus = A \times M$). Under specialization, hunters get acquisition incentive only ($Bonus = A$) and farmers earn maintenance incentive only ($Bonus = M$). Figure 6 shows that under specialization,

Figure 6 Counterfactual on Job design: Multi-tasking vs. Specialization



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

hunters acquire more bad loans and thus the share of bad loans goes up (Figure 6a). Worse, farmers cannot collect the bad loans, thus the repayment probability goes down (Figure 6b). The net present value of loans goes down by 35% under specialization (Figure 6c). The mechanism is two-part: (i) hunters exploit private information fully under specialization without concern for repayment by acquiring bad loans. (ii) farmers are very good at collecting good loans, but particularly bad at collecting bad loans, so most of the bad loans acquired by hunters are not collected. Together this leads to a massive reduction in repayment and NPV.

Table 7 Counterfactual on Job design: Multi-tasking vs. Specialization

Job Design	Multitasking			Specialization		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	104.1	109.8	105.9	133.7		133.7
Acquisition - Bad	230.3	112.3	192.5	308.2		308.2
Maintenance - Good	88.4	91.2	89.3		132.4	132.4
Maintenance - Bad	139.8	86	122.6		79.7	79.7
Net Present Value (NPV)	422.8	365.9	404.6			261.9

1) Multi-tasking Incentive Plan: $Bonus = A \times M$
2) Specialization Incentive Plan: $Bonus = A$ for Hunter and $Bonus = M$ 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 8%.

6.4.2. Incentive Design: We compare outcomes under the current multiplicative incentive scheme ($Bonus = A \times M$) against an additive incentive scheme ($Bonus = A + M$). Table 8 reports acquisition/maintenance performance of each segment of salespeople on good and bad loans; and Net Present Value (NPV) that captures profitability. Figure 7, where we visualize the counterfactual results, shows that for hunters, the repayment probability and firm profits are higher under the multiplicative scheme. This is as expected based on the argument in MacDonald and Marx (2001)) that the multiplicative scheme mitigate the temptation for adverse specialization where hunters focus more on acquisition, and particularly on bad loans, which are least costly for them to acquire.

However, surprisingly, for farmers the results are reversed and repayment probability and NPV is higher with the additive scheme. At the acquisition stage it is equally costly for farmers to acquire good and bad loans, hence more loan acquisition yields proportionately have more bad loans. Farmers recognize their inability to collect bad loans and even with the additive plan they limit the number of loans acquired that internalizes their inability to collect future bad loans. However, the additional complementarity induced by the multiplicative incentive scheme forces farmers to acquire more loansbecause low acquisition will lead to low payoffs even if repayment is high. But this increases the number of bad loans in the portfolio–leading to lower repayment and lower profitability with the multiplicative scheme. Our insight that multiplicative incentive scheme can make the firm worse off under some conditions is theoretically novel and contributes to a better understanding of the role of payoff complementarity in incentives.

Overall, given that hunters are a greater proportion of the salesforce at the firm, the total profits for the firm under the multiplicative incentive scheme is greater.

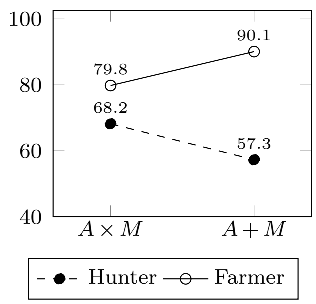
Table 8 Counterfactual on Incentive design: Multiplicative vs. Additive

Incentive Design	Multiplicative ($Bonus = A \times M$)			Additive ($Bonus = A + M$)		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	104.1	109.8	105.9	93.6	87.5	91.6
Acquisition - Bad	230.3	112.3	192.5	202.3	115.6	174.6
Maintenance - Good	88.4	91.2	89.3	79.6	86.9	81.9
Maintenance - Bad	139.8	86	122.6	89.9	96.1	91.9
Net Present Value (NPV)	422.8	365.9	404.6	266.6	404.2	310.6

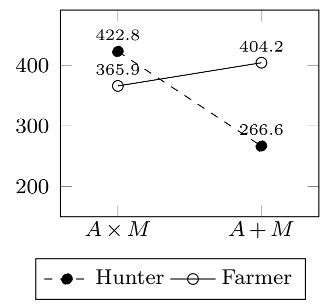
1) Aggregate measures take account of share of hunters (68%) and that of farmers (32%) in the setting.
2) All values are in 1,000 pesos.
3) NPV is based on monthly interest rate of 8%.

6.4.3. Private Information and Transfers: Finally, we investigate the impact of job transfers through its impact on eliminating the salespersons private information about customers. Table 9 and Figure 8 compare salesperson performance and profitability when

Figure 7 Counterfactual on Incentive design: Multiplicative vs. Additive



(a) Repayment Probability (%)



(b) NPV (1000 Pesos)

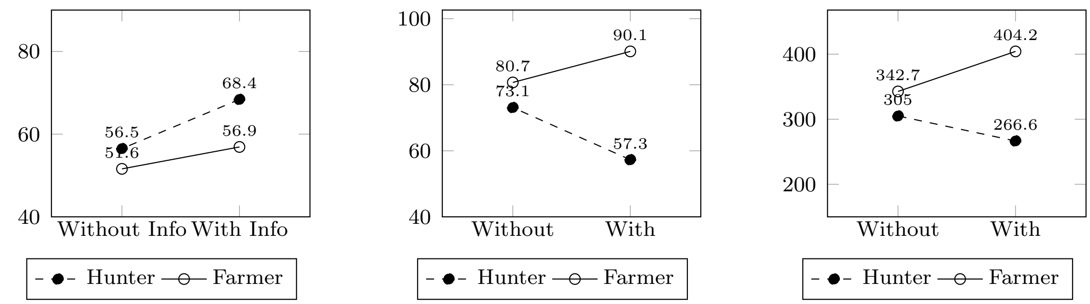
they do not have private information vs when they do. With private information, hunters abuse their knowledge to acquire more bad loans (Figure 8a), which are repaid less (Figure 8b) and generate lower profit (Figure 8c). Farmers, however, take advantage of private information to slightly increase the share of bad loans (Figure 8a), selectively monitor and collect loans well (Figure 8b) and generate higher profit (Figure 8c). Thus, our 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.

Table 9 Counterfactual on Transfer Policy: Without vs. With Private Information

	Without Private Information			With Private Information		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	93	98.9	94.9	93.6	87.5	91.6
Acquisition - Bad	121	105.3	116	202.3	115.6	174.6
Maintenance - Good	73.4	84.4	76.9	79.6	86.9	81.9
Maintenance - Bad	83	80.4	82.2	89.9	96.1	91.9
Net Present Value (NPV)	305	342.7	317	266.6	404.2	310.6

1) Incentive plan: $Bonus = A + M$ to highlight adverse specialization
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 8%.

Figure 8 Counterfactual on Transfer Policy: Without vs. With Private Information



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

7. Conclusion

We develop the first structural model of a multi-tasking sales force with multi-dimensional sales incentive and private information. We find two segments of salespeople who respond differently to the acquisition and repayment incentives in a microfinance bank setting. The unique feature of our model is the intertemporal effort dynamics, induced by (i) the multi-tasking job that requires effort allocation and (ii) salesperson private information about customers. We adapt and extend two step estimation approaches to allow for multidimensional effort, incentives and private information. Our counterfactual simulations provide practical guidelines on (i) salesperson job design, (ii) combine performance outcomes for multi-tasking salespeople, and (iii) job transfers. Our model and framework is adaptable to model salespeople in CRM settings, where salespeople are responsible for customer acquisition and retention, and have private information about customer profitability.

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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 the maintenance index depending on the share of loan amount in good standing in each period.

Table A1 Maintenance Index

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

B. 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 A2, replicated from Kim et al. (2018), 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.[22]

C. Deep IV in Loan Type Inference

We use instrument variables (e.g., transfer status, average IRR of the other loans acquired/maintained by the same salesperson in the same period) to handle the endogeneity in the prediction of ex ante loan profitability (equation (7)). Standard 2SLS runs two consecutive OLS regressions to get an IV estimator (the first regression of endogeneous variables $State_{j(i)t...T(i)}$ on instrument variables $Z_{j(i)t...T(i)}$ to get $\hat{State}_{j(i)t...T(i)}$ and the second regression of dependent variables IRR_i on $\hat{State}_{j(i)t...T(i)}$) by assuming the linear mapping between $State_{j(i)t...T(i)}$ and $Z_{j(i)t...T(i)}$ and the linear relationship between IRR_i and $\hat{State}_{j(i)t...T(i)}$. To relax the assumptions on the functional forms,[23] we use Deep IV (Hartford et al. 2017)[24] that uses deep learning approach (neural network) in IV estimation. The detailed procedure is as follows.

[22] The exact values of the coefficients are slightly different from those reported in Kim et al. (2018). 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.

[23] We could use a nonparametric IV method not to impose the functional form restriction (e.g., Newey and Powell 2003), but the method still requires an assumption on the data generating process and does not handle many input variables well.

[24] The paper does not provide statistical properties of the estimates. They experimentally evaluate the trade-off between the (potential) cost of asymptotic performance and lower variance.

Table A2 Randomness of Transfer

	DV: Transfer					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquisition Index (t-1)	-0.253		-0.256			-1.605
	(0.274)		(0.276)			(1.213)
Maintenance Index (t-1)		0.00725	0.0490			1.145
		(0.474)	(0.475)			(2.458)
Tenure				0.000222		0.00903
				(0.00488)		(0.0151)
Time Since Last Transfer					-0.399	-0.279
					(0.350)	(0.313)
Intercept	-2.865***	-3.060***	-2.903***	-3.207***	-3.132***	-3.383
	(0.488)	(0.593)	(0.609)	(0.164)	(0.836)	(2.410)
Period FE	Yes	Yes	Yes	No	No	No
N	1637	1640	1637	2352	306	256
Pseudo R^2	0.120	0.119	0.120	0.000	0.032	0.076

Step 1. Learn the conditional distribution of salesperson states given loan characteristics and instrument variables, using neural network: $\hat{F} = F_\psi(State_{j(i)t...T(i)}|L_i, S_{j(i)}, Z_{j(i)t...T(i)})$, where ψ is the network parameter. For the simplicity, we discretize $State_{j(i)t...T(i)}$ into 10 values and estimate the conditional probability $\hat{P}(State^w) = Prob(State_{j(i)t...T(i)} = State^w|L_i, S_{j(i)}, Z_{j(i)t...T(i)};\psi)$ where $w = 1,2,...,10$.

Step 2. Optimize the network parameter η by minimizing the difference between observed and predicted loan profitability, using the network parameter ψ from step 1.

$$L(\eta) = \frac{1}{I}\sum_i (IRR_i - \sum_{w=1}^{10} h(State^w, L_i, S_{j(i)};\eta)\hat{P}(State^w;\psi))$$

where I is the number of loans in the data and $\hat{P}(State^w;\psi)$ is estimated from step 1.