A STRUCTURAL MODEL OF A MULTITASKING SALESFORCE: MULTIDIMENSIONAL INCENTIVES AND PLAN DESIGN

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September 2019

COWLES FOUNDATION DISCUSSION PAPER NO. 2199

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The paper broadens the focus of empirical research on salesforce management to include *multitasking* settings with *multidimensional incentives*, where salespeople have *private information* about customers. This allows us to ask novel substantive questions around multidimensional incentive design and job design while managing the costs and benefits of private information. To this end, the paper introduces the first structural model of a *multitasking* salesforce in response to *multidimensional incentives*. The model also accommodates (i) dynamic intertemporal tradeoffs in effort choice across the tasks and (ii) salesperson's private information about customers. We apply our model in a rich empirical setting in microfinance and illustrate how to address various identification and estimation challenges. We extend two-step estimation methods used for unidimensional compensation plans by embedding a flexible machine learning (random forest) model in the first-stage multitasking policy function estimation within an iterative procedure that accounts for salesperson heterogeneity and private information. Estimates reveal two latent segments of salespeople–a "hunter" segment that is more efficient in loan acquisition and a "farmer" segment that is more efficient in loan collection. Our counterfactuals assess (i) performance combination across tasks (multiplicative versus additive); (ii) multitasking versus specialization in job design; and (iii) job transfers that impact private information.

Key words: Salesforce compensation, multitasking, multidimensional incentives, job design, private information, adverse selection, moral hazard, personnel economics, organizational economics

1.   Introduction

Personal selling employs approximately 10% of the US labor workforce; selling-related expenditures are about 5% of the US GDP at approximately $1 trillion (Zoltners et al. 2008). These shares are even greater in the retail, financial services, automobiles, banking, consulting, and technology sectors (Misra 2019). As a benchmark, the total advertising spending in the United States as of 2019 is around $200 billion. Despite the potential for substantial gains from effective salesforce management, research remains limited relative to advertising. Recently, the availability of rich data on compensation plans and salesforce performance has led to a spurt of empirical research (e.g, Misra and Nair 2011, Chung et al. 2013, Chan et al. 2014) but these papers only study single task salesforces with incentive plans based on *unidimensional* metrics of performance (e.g., sales). A recent survey of compensation practices, however, showed that over 86% of firms use multiple metrics of performance for salesforce compensation (WorldatWork 2016). Further, this literature has not considered the efficiency–moral hazard concerns arising from private information that salespeople have about customers relative to the firm—arising from their greater proximity and ongoing relationships with customers.

In this paper, we broaden the focus of empirical research in salesforce management to include multitasking settings with multidimensional incentives, where salespeople have private information about customers. This allows us to ask novel substantive questions around (i) design of multidimensional incentives (ii) task allocation and job design and (iii) managing the costs and benefits of salesperson's private information. To this end, the paper introduces the first structural model of a *multitasking* salesforce in response to *multidimensional incentives*. The model also accommodates (i) dynamic intertemporal tradeoffs in effort choice across the tasks and (ii) salesperson's private information about customers. Finally, we apply our model in a rich empirical setting in microfinance and illustrate how to address the various identification and estimation challenges involved in estimating such a model. The features of the model and our solution to various estimation challenges considerably expand the range of employee incentive problems and settings for which structural modeling can be applied.

We first elaborate on the three substantive questions we address, and then describe the empirical context to motivate the critical and novel features of our structural model. In terms of substantive issues, we first consider the design of multidimensional incentives for

multitasking employees. In practice, firms typically aggregate performance across multiple tasks (or performance dimensions) additively using a weighted average of performance on each task (e.g., Hong et al. 2018, Bartel 2017, Lu 2012). Researchers also mostly model additive aggregation (e.g., Holmström and Milgrom 1991, Athey and Roberts 2001, Bond and Gomes 2009, Ederer et al. 2018). However, when there are production complementarities across tasks, additive aggregation can lead to misalignment between the salesperson and firm incentives. As MacDonald and Marx (2001) show, if the salesperson's payoffs do not consider the production complementarities across tasks, the salesperson considers each task as a substitute for the other, and allocates more time on the task that is easier for her at the expense of the firm; they dub this focus on the easier task even when the firm prefers more distributed effort across tasks as "adverse specialization." Therefore, in jobs involving production complementarities across tasks, incentive design should consider ways to induce payoff complementarities across tasks to improve incentive alignment. One approach we will consider to create payoff complementarities and reduce misalignment is to use multiplicative aggregation because payoffs will be higher when efforts are allocated more equally across tasks. This is particularly relevant in our empirical context because the focal firm uses multiplicative aggregation of performance across tasks.

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

Finally, we consider how firms can manage the costs and benefits of the salesperson's private information. Private information can benefit the firm if salespeople can use it to

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[1] It is potentially possible to have teams of employees be responsible for the joint outcomes across multiple tasks, with individual salespeople specializing in a task. In this paper, we abstract away from team-based job design.

be more productive, but it can also hurt the firm when salespeople use it to generate compensation at the expense of the firm. For example, if a salesperson has private information about a customer's ability to repay a loan, acquiring such a loan when the private information is unfavorable will help the salesperson gain short-term commissions at the expense of the firm profitability. A standard tool used by managers is to periodically transfer employees out of their territories to eliminate their private information. We evaluate the costs and benefits of using periodic transfers for firms.

Our empirical application is in the context of a microfinance institution's salesforce (loan officers) that is responsible for both loan acquisition and loan collection. The context has close parallels to the customer relationship management (CRM) literature, in which sales employees may either specialize or be jointly responsible for customer acquisition and retention. The empirical context requires us to incorporate two significant features into our structural model of multitasking. The first is a "dynamic intertemporal tradeoff" in effort allocation across new loan acquisition and repayment tasks when there is heterogeneity in loan repayment probabilities. For example, a salesperson acquiring easier-to-acquire loans today to do well on the acquisition metric must be concerned about the tradeoff on future payoffs because such a customer is less likely to repay the loans. The second is "private information." Salespeople have private information about their customers' profitability unavailable to the firm, and this information can impact their choice of effort allocation across tasks. While private information may help improve efficiency by allowing salespeople to target the right customers for acquisition and repayment, it can also lead to incentive 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.

Beyond modeling, these two features also have relevance for our substantive questions. The dynamic intertemporal tradeoff between acquisition and repayment produces a production and payoff complementarity, especially in the presence of private information because firms have less information than salespeople about whether a loan is more likely to be good or bad. Putting in more effort to acquire good loans means less effort is needed to maintain those loans for the salesperson. As discussed before, the production complementarity between the acquisition and repayment tasks has implications for job design. Further, given the inbuilt payoff complementarity in performance across the two tasks, it is theoretically

and empirically interesting as to why our focal firm uses multiplicative aggregation of performance on loan acquisition and repayment. We assess whether multiplicative aggregation is needed to improve alignment and whether additive and multiplicative aggregation have qualitatively different effects on loan officer segments with different relative costs for tasks.

We estimate the structural model of multitasking by loan officers at the bank using data on salesforce performance and compensation matched with the loans generated by the loan officers and information about the loan characteristics and repayment outcomes. It is useful to consider the features of the data that allow us to incorporate features such as multitasking and private information relative to the existing structural literature on salesforce compensation. First, in contrast to the existing literature, which observes only sales performance outcomes, we observe not only new loan acquisition volumes but also the repayment performance on past loans, which allows us to model the multitasking effort in both acquisition and maintenance to collect loans. Second, there are several features of the data that allow us to study the role of private information. We observe ex-post loan repayment behavior for individual loans in combination with ex-ante loan characteristics, and salesperson states that impact incentives to exploit private information at the time of loan acquisition and maintenance. By controlling the effect of observed ex-ante loan characteristics and salesperson states, we can back out the unobservable private type of each loan. Further, the bank's random transfer policy creates an exogenous variation on whether salespeople have private information, which allows us to identify differences in effort allocated when salespeople have private information or not. While this variation is not necessary for model identification, it provides overidentifying restrictions for the structural model and descriptive evidence in support of differences in behavior that is consistent with the structural model's predictions when there is no private information.

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

Next, we explain the estimation challenges in accommodating multitasking and private information and how we address them. First, with multitasking (acquisition/maintenance)

and private information (good/bad loans), salespeople must decide on four levels of effort related to the acquisition and maintenance of good and bad loans. Hence, the nonparametric first stage estimation is significantly more complicated than in Chung et al. (2013) who use a Chebyshev polynomial approximation. Here we use a machine learning model— random forest with cross-validation— for flexibly estimating the first-stage nonparametric effort policy functions while avoiding overfitting. Second, although the salesperson has private information about loans and hence can tell ex-ante loan types, the researchers cannot directly observe it. A particular challenge here is that salespeople can affect loan outcomes through their effort choices. Hence, we need to infer ex-ante loan types from *ex post* loan outcomes, controlling for the salesperson's state variables and the salesperson's latent class. We develop an algorithm to jointly infer the ex-ante loan types and the salesperson's latent class in the first stage of the two-step estimation procedure.

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

Our first counterfactual shows a nuanced tradeoff in the heterogeneous relative impact of additive versus multiplicative aggregation of performance across tasks. Consistent with the insights in MacDonald and Marx (2001), we find that the multiplicative aggregation (which induces additional payoff complementarities over the additive aggregation) helps the firm avoid adverse specialization by preventing the *hunter* segment from focusing excessively on acquiring new loans, especially bad ones. However, the multiplicative aggregation backfires with the *farmer* segment due to their high (low) cost to acquire (maintain) loans by forcing them to spend more effort on the acquisition, generating more bad loans that become delinquent than they would have with additive aggregation. Our results thus add theoretical nuance to the additive versus multiplicative aggregation debate.

Our second counterfactual examines a largely unexplored managerial question in the salesforce literature on the allocation of tasks across salespeople with heterogeneous capabilities. In particular, we address the specialization–multitasking tradeoff in job design.

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

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

The rest of the paper is organized as follows. Section 2 describes the related literature and positions the current paper. Section 3 describes the institutional setting and data. Sections 4 and 5 describe the model and estimation respectively. Section 6 discusses the model estimates while Section 7 reports the findings from counterfactuals. Section 8 concludes.

2. Related Literature

Our paper contributes to several streams of literature. First, our paper is related to the theoretical literature on the multitasking principal-agent model (see, e.g., Holmström and Milgrom 1991, Baker et al. 1994, Dixit 2002). A key finding of this literature is that incentivizing one dimension of multiple tasks may lead to the agent shirking on other performance dimensions. Holmström and Tirole (1993), for example, find that incentive schemes that reward only immediately realized profits can lead agents to sacrifice long-run profits. To solve this moral hazard problem, Godes (2004) proposes the division of labor for salespeople who work on technologically substitutable tasks. MacDonald and Marx (2001) consider the case of multitasking with production complementarities across tasks. Here the principal prefers the agent to spread effort across tasks, but the agent prefers to spend more effort only on less costly tasks under and additive performance aggregation based scheme. They refer to this outcome as "adverse specialization" and therefore suggest the need for incentive contracts that have payoff complementarity across task outcomes to improve incentive alignment with the principal. Our focal firm uses multiplicative performance aggregation, which naturally induces payoff complementarities. However, in our

application, even with additive incentives, there are payoff complementarities. We, therefore, assess whether multiplicative aggregation is needed to improve alignment and whether additive and multiplicative aggregation have qualitatively different effects on loan officer segments with different relative costs for tasks.

The second stream of literature related to our study is the empirical literature on studying multitasking agents. Agarwal and Wang (2009) and Agarwal and Ben-David (2018) exploit an exogenous change in the compensation structure of a bank in the US to show that sales incentives encourage loan officers to take excessive risk and increase defaults. To address this issue, they argue that incentives must be complementary in terms of performance across multiple tasks. Using commercial bank data, Behr et al. (2019) find that the multidimensional contract is effective for stimulating overall greater effort. Kim et al. (2019) study the same bank setting like ours and find evidence of private information that leads to salesperson moral hazard in the form of adverse loan selection, i.e., salespeople's acquisition incentives incentivize them to acquire low-quality loans. They also find that because loan officers are responsible for loan maintenance as well as acquisition, the maintenance incentives mitigate the adverse selection in loans. In contrast, Bracha and Fershtman (2012) do not find evidence of a distorting effect of the multi-dimensional pay-for-performance scheme. Our paper adds to the literature by developing a structural framework to address multitasking dynamics in the presence of private information.

To the best of our knowledge, empirical work on job design remains scarce despite a highly influential theoretical paper by Holmström and Milgrom (1991). A notable exception is Baker and Hubbard (2003), who study the effect of new technology on asset ownership and job design in the trucking industry. Our paper contributes to this literature by evaluating task allocation schemes in job design using the dynamic structural framework. Interestingly, making salespeople responsible for managing ongoing customer relationships can be thought of as giving salespeople an "ownership stake" in the customers they acquire, and thus incentivizing them to acquire better customer "assets" and maintain them.

Our paper is most closely related to the empirical literature on salesforce compensation. Although the early work tended to take the form of descriptive analyses of salesforce compensation practices and involve testing predictions of the principal-agent theory in compensation plan design (e.g., Joseph and Kalwani 1998, Coughlan and Narasimhan 1992), there has recently been a surge of work that estimates structural models using

data from salesforce performance outcomes in response to incentive schemes at the firm (e.g., Misra and Nair 2011, Chung et al. 2013, Schöttner 2016). As discussed before, these papers have been focused on single-task salesforces. By expanding our focus to multitasking with multidimensional incentives accounting for intertemporal dynamics across tasks and private information, the paper considerably expands the salesforce and employee incentive settings in which structural modeling can be applied. In marketing, the features of our model can be easily adapted to managing salesforces in CRM settings, where firms need to balance customer acquisition, retention, and growth over time.

3. Institutional Setting and Data

This section describes the institutional setting, provides details of the data and descriptive evidence in support of the modelling choices.

3.1. Institutional Details

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

The bank hires salespeople to accomplish two tasks: acquiring new loans and collecting repayments. The empirical setting is ideal for studying multitasking because the loan officers at the bank are jointly responsible for both loan acquisition and loan maintenance to ensure repayment. 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 gives the loan officers discretion in not only whether to approve a loan, but also the terms of the loan (e.g., loan amount, loan duration). The bank only decides on the interest rate based on public information about the borrower (i.e., a $1-5$ credit rating with 5 as best, constructed with data from an external agency) and its history with the customer. Hence, loan officers have no incentive to misreport. At the maintenance stage, the loan officers use phone calls and in-person visits to ensure timely repayments.

Salesperson j's monthly compensation in period t is denoted as $W_{jt}(1 + B_{jt})$, where fixed salary (W_{jt}) is determined solely by seniority, not performance, and bonus index (B_{jt}) depends on customer acquisition and maintenance performance. The bonus is bounded below by zero and is incremental to salary; hence the loan officers have limited liability.

Acquisition performance is benchmarked against one's past performance to generate an acquisition index (Acquisition index A_{jt} is defined as $A_{jt} = N_{jt}/Q_{jt}$ where N_{jt} is the amount of new loans acquired by officer j at period t, and Q_{jt} is the acquisition quota, which depends on the amount of existing loans of officer j at the beginning of period t).

Maintenance index is based on the value of collected loans relative to that of outstanding loans $(M_{jt} = g(R_{jt}/O_{jt}))$, where R_{jt} is the amount of repaid loans collected by officer j, O_{jt} is the outstanding value of loans in salesperson j's portfolio due at period t, and $g(.)$ is an increasing step function detailed in Table A1 in the appendix. The final bonus is the product of the base salary, acquisition index, and maintenance index (i.e., $B_{jt} = W_{jt}A_{jt}M_{jt}$); thus, receiving zero points in any category would earn no bonus at all. Note that the maintenance index, which holds the salesperson account for repayment of the loans that she acquired, aligns the incentive between the salesperson and the firm. Using the index, the firm effectively transfers the partial ownership of an ongoing asset to salespeople.

Since the bonus incentives are based on a combination of acquisition and maintenance performance, the officers have to not only balance their efforts between acquisition and maintenance tasks at each point of time, but they also have to consider a dynamic intertemporal trade-off between the short-term benefits of acquiring (possibly lower quality) customers to improve acquisition performance and its long-term adverse effects on maintenance performance.[2]

In our setting, loan officers obtain private information about customers' quality, unobservable to the firm, since customer engagement with the bank exclusively happens through salespeople at customer premises. Salespeople not only infer customers' motives, needs, financial capabilities/liabilities, and outside options, but also observe how well each customer is running his business, or if a customer is experiencing unexpected financial hardship.[3] It is almost impossible for the bank (or its managers) to access such private infor-

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[2] Theoretically salespeople may game the timing of loan acquisition, but given the borrower's liquidity constraints in microfinance settings, this is practically a second-order effect. We abstract away from the issue in this paper.

[3] Salespeople acquire private information not just on existing loans but also on prospects for new loans. This is because new loans are often given to repeat customers, salespeople interact with new prospects during the learning period. Furthermore, knowledge of the neighborhood (e.g., market condition, demand, competition) gained during the learning period helps officers make better inference about new customers' financial credibility.

mation. Salespeople can use the private information in allocating effort on acquiring and maintaining loans because it affects the salesperson's payoff through its direct impact on the probability of delinquency and the cost of acquiring and maintaining loans.

In retail banking, transfers are used as a standard policy to avoid potential abuse of private information by loan officers through adverse selection in new loans to customers (Fisman et al. 2017). Our focal bank also follows a transfer policy; however, it goes further than typical banks in that who is transferred and where they are transferred to are entirely random by design. This prevents loan officers from engaging in potential moral hazard behaviors when they expect to be transferred. Such "instant" transfers are feasible because the bank operates within one large metropolitan area.

A (randomly) transferred salesperson takes over and monitors the loans acquired by the predecessor who left the branch. After a transfer, the transferred salesperson's maintenance performance is assessed only on the loans at the new branch she took over, thus making her portfolio exogenous upon transfer. Justified by descriptive evidence, we assume that there is a learning period after transfer for salespeople to acquire private information; during the learning period, they do not have any private information.

3.2. Data

Our data consist of the following: (1) salesperson-level data that contain each salesperson's characteristics, and monthly performance and compensation as analyzed in the previous empirical salesforce compensation literature and (2) loan-level transaction data that contain each loan's characteristics and monthly repayment outcomes. The two datasets are matched based on the identity of a salesperson who originates or monitors each loan in each period.[4] The data we use for estimation include the performance and compensation outcomes of 229 salespeople over a 14-month period from January 2009 to February 2010. In all, we obtain 2,648 observations (months of performance outcomes and compensation) across the 229 salespeople. The performance and compensation outcomes are aggregated/summarized from the 100,250 loans for which we observe detailed repayment outcome data over the life of the loan.

Table 1 reports summary statistics of our salesperson panel data. Out of the 2,648 salesperson-month observations in the data, 4.8% of observations have transfers. A total of

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[4] Salespeople were removed from the final sample if their aggregate performance did not match with the compensation index, possibly because loans that contributed to their bonus are missing in our data. We also dropped 29,589 loans from the data that could not be matched to salespeople.

22.3% of the salespeople experience at least one transfer during our 14-month observation window. The average tenure is 25.5 months, and they acquire 347,470 pesos (approximately US$25,365 as of 2009) of new loans, have 888,300 pesos (approximately US$64,845) of loans in the portfolio and collect 772,847 pesos (approximately US$56,415) in repayment each month. The acquisition index benchmarked against the quota is 0.82 on average (i.e., salespeople achieve 82% of quota on average), and the maintenance index benchmarked against the amount of loans in the portfolio is 0.86 on average. On average, the loan officers' bonus was 55% of their salary. Figure 1 displays the distribution of Acquisition, Maintenance, and Bonus indices.

Table 1   Summary of Loan Officer Characteristics and Performance

	N	Distribution			
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	772.8	695.8	0	5052.7
Acquisition Quota (1000 pesos)	2648	429.2	492.8	13.2	2938.8
Acquisition Index (A)	2648	0.82	0.42	0.02	3.19
Maintenance Index (M)	2648	0.86	0.23	0	1.25
Bonus Index ($A*M$)	2648	0.55	0.3	0	2.35

Figure 1   Distribution of Bonus Indices

(a) Acquisition Index   (b) Maintenance Index   (c) Bonus Index
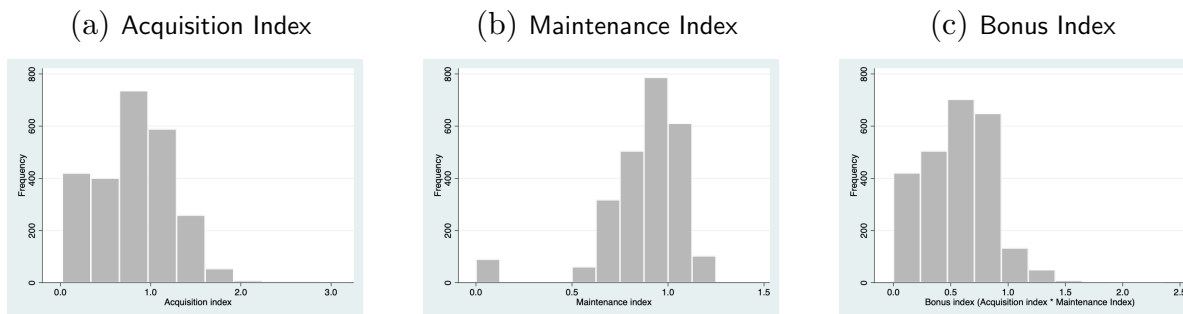
According to the firm's policy, the acquisition quota, Q_{jt} is a function of the amount of outstanding loans in salesperson j's portfolio at the beginning of period t, O_{jt}, and the lagged acquisition quota $Q_{j,t-1}$. Since we do not know the exact formula for the acquisition quota Q_{jt}, we will infer the transition of quota based on the observed data.

Next, Table 2 summarizes the distribution of loans, performance, and loan terms by credit rating. The credit rating information comes from an external credit agency, and the agency determines it based on the borrower's financial history across institutions. Most of the loans are given to customers with the highest credit rating. As expected, loan performance, as measured by ex-post IRR, and delinquency probability of each loan is highly correlated with credit rating. Thus, we expect the proportion of good type loans to increase by credit rating monotonically. As for the loan terms, interest rates are roughly the same across credit ratings. This is because the interest rates are determined by the firm based on the borrower's history with the firm, and all first-time borrowers typically start at the highest rate, and the rate goes down if they repay loans well. The loan amount has a very high standard deviation across all credit ratings, and there is no systematic relationship between the loan amount and credit ratings. Lastly, loan duration tends to be shorter for borrowers with a better rating.

Table 2 Loan Performance and Terms by Credit Rating

Rating	N	IRR		Delinquency Pr.		Interest rate		Amount		Duration	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	3,269	45.68	44.62	0.72	0.35	88.63	9.82	783.98	621.22	10.2	6.31
2	2,125	53.15	39.59	0.67	0.36	86.46	9.51	1051.75	977.73	10.11	6.63
3	5,110	67.12	35.68	0.5	0.38	87.97	8.63	979.26	848.33	8.03	4.16
4	18,127	79.17	24.02	0.27	0.31	85.99	7.34	863.96	877.04	5.9	3.62
5	71,619	87.45	19.7	0.16	0.22	87.76	19.7	866.28	862.45	5.66	3.23

3.3. Descriptive Evidence

In this section, we first verify that transfers are indeed random as per firm policy and, therefore, exogenous to loan officer characteristics and performance. We then present descriptive evidence for two key features underlying the structural model— (i) how salesperson's private information, driven by transfer, affects her choice of acquisition and maintenance effort of each loan type; and (ii) how salesperson's current portfolio shapes her maintenance pressure, which impacts her choice on acquisition effort and maintenance effort of each loan type.

3.3.1. Randomness of Transfers: As noted earlier, the firm's transfer policy is by design, random in terms of timing and transfer location. We verify this by testing whether the transfer at time t for a salesperson j can be predicted by the salesperson's performance

(acquisition or maintenance index) in the previous period, tenure, or length of time since last transfer. Table 3 reports the results of logistic regression and shows that none of these variables are significant, verifying that the firm policy was indeed random. Given this, we treat random transfers as exogenous variation in salesperson private information.

Table 3   Randomness of Transfer

	(1)	(2)	(3)	(4)	(5)	(6)
			DV: Transfer			
Acquisition	-0.253		-0.256			-1.605
Index (t-1)	(0.274)		(0.276)			(1.213)
Maintenance		0.00725	0.0490			1.145
Index (t-1)		(0.474)	(0.475)			(2.458)
Tenure				0.000222		0.00903
				(0.00488)		(0.0151)
Time Since					-0.399	-0.279
Last Transfer					(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

3.3.2.   Effect of Private Information on Acquisition and Maintenance Performance: To assess whether the loss of private information after a transfer impacts effort allocation, we test whether the IRR of loans acquired and the probability of loan delinquency at the time of maintenance (conditional on credit rating) differ during the learning period when there is no private information. Assuming a one month learning period for private information (see Appendix B for the analysis that justifies this assumption), Figure 2a shows that the loans acquired by salespeople with private information have a lower ex-post IRR than those acquired by the salespeople without. This suggests that salespeople use their private information to selectively bring in lower-quality loans, which are easier to acquire. Moreover, Figure 2b shows that the average delinquency probability of loans collected by the salesperson when they have private information is lower than when they do not. Thus, salespeople use their private information to selectively collect loans that are well maintained upon effort. This implies that private information can either benefit or hurt the firm's profit: it can help increase efficiency by allowing salespeople to target the right customers for maintenance, but enhance the incentive misalignment between sales-people and the firm by encouraging salespeople to selectively acquire the easier-to-acquire, less profitable customers. More detailed regressions that control for loan and salesperson

observables, incentive states, and fixed effects; replicate the robustness of these conclusions can be found in Kim et al. (2019).

Figure 2   Effect of Private Information (Learning period: one month after transfer)

(a) On Acquired Loan Quality

(b) On Loan Delinquency at Maintenance
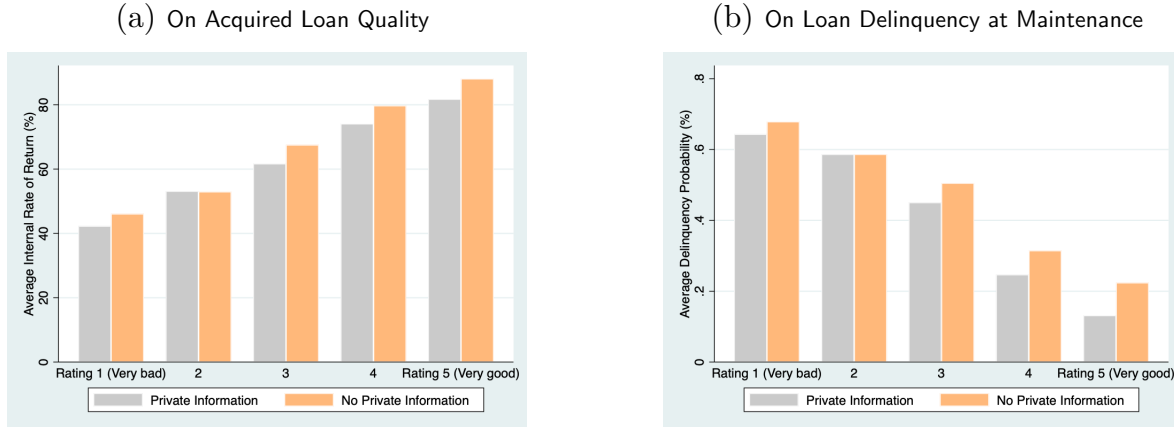
3.3.3.   Effect of Maintenance Pressure on Loan Performance: Next, we provide descriptive evidence on how the use of maintenance performance for incentives impact acquisition and maintenance behavior. To graphically show the evidence, we divide periods into two groups based on the level of maintenance pressure. We consider a salesperson is under *high* maintenance pressure in period t, if her portfolio is composed of more delinquent loans than usual, i.e., the ratio of the amount of delinquent loans to the amount of outstanding loans at the end of period $t-1$ was higher than her median value of the ratios across periods. Figure 3a shows the acquired loans' quality as a function of credit rating by maintenance pressure. The loan quality is represented by the average *ex post* annual IRR of loans acquired in period t on the vertical axis. The horizontal axis has the loans' public credit rating. Note that the maintenance pressure is measured at the time of loan acquisition, and the acquired loans' ex-post IRR is measured after the loan cycle is completed. The average IRR of the acquired loans is higher when the share of delinquent loans is above the median for every rating level. In other words, a loan officer is likely to acquire higher-quality loans under higher pressure of ensuring sufficient repayment from the loans in their portfolio. Figure 3b shows the average delinquency probability of loans when a salesperson collects loans under high and low maintenance pressure. Note that the maintenance pressure and the loan delinquencies are measured in the same period. The

Figure 3   Effect of Maintenance Pressure

(a) On Acquired Loan Quality   (b) On Loan Delinquency at Maintenance
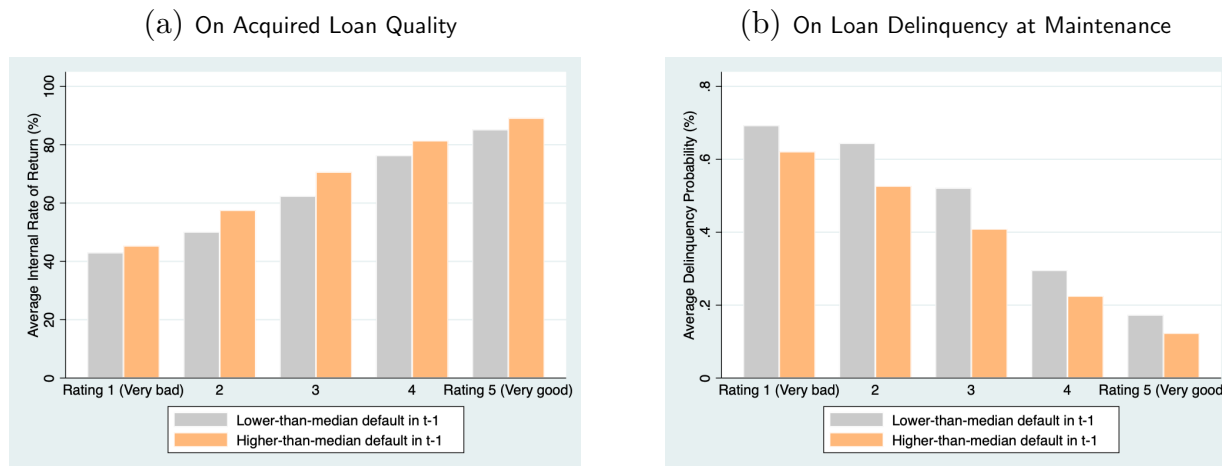
average delinquency probability is higher (lower) for the salespeople under lower (higher) pressure, who have lower-than-median delinquent loans in their portfolio.

These graphs show that maintenance pressure affects both the salesperson acquisition and maintenance effort. Therefore, we include the salesperson's portfolio states, such as the amount of delinquent loans or the amount of outstanding loans in each period, as state variables in the effort policy functions.

4.   Model

Given the above descriptive evidence, we now develop a dynamic structural model of a multitasking salesforce in the presence of private information. A salesperson exerts effort on acquisition and maintenance tasks in response to the multidimensional incentive scheme discussed above. Further, the salesperson with private information about customer profitability takes into account the dynamic trade-off of acquiring or maintaining different types of loans. The loan types are private information to the salesperson. While bad (riskier) (conditional on public information) loans are easier to acquire, they are more likely to go delinquent in the future, thus hurting maintenance performance and requiring greater maintenance effort in the future. We model unobservable ex ante loan types in the population as a discrete binary distribution—"good" (ex-ante profitable, harder-to-acquire loans) and "bad" (ex-ante unprofitable, and easier-to-acquire loans), where the proportion of good types in the population can vary by observable credit rating.

Figure 4 describes the timing of the model within a period (month). For a salesperson, each period is either a learning period (where she does not have private information) or

Figure 4   Within-Period Timing of Salesperson Model
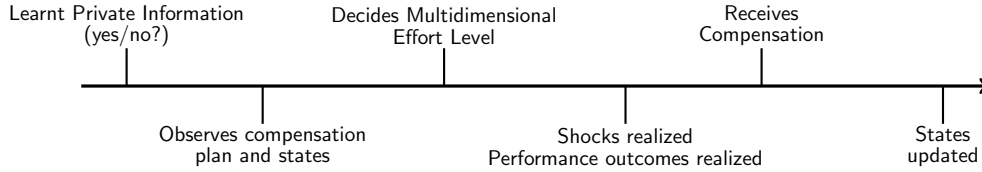
a non-learning period (where she has private information). The salesperson observes the compensation plan and her states in the period. Over the period, the salesperson chooses effort level on the multiple dimensions–and this varies by whether the salesperson has private information or not. At the end of the period, the outcomes are realized depending on both effort and shocks, and then the salesperson receives compensation based on the realized performance outcomes. Lastly, the states are updated based on the realized outcomes. The model repeats every period.

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

4.1.   Private Information

In this section, we describe how we operationalize the presence or absence of private information. Based on our descriptive evidence, we treat the month right after transfer as a learning period without private information for that salesperson and all other periods as periods with private information about loan types (good or bad). Since transfers are uncorrelated to loan officer characteristics and performance, the presence or absence of private information is exogenous in the model.[5]

4.2.   Compensation Plan

The salesperson receives a fixed monthly salary and a bonus.[6] The bonus is based on composite performance along the acquisition and maintenance tasks. Acquisition performance

---

[5] We exploit random transfers in our empirical setting to treat private information as exogenous and deterministically classify periods as those with private information versus not. More generally, the presence or absence of private information can be probabilistically modeled using exogenous instruments (even at the level of each consumer), and integrated over the probabilities to model performance outcomes with and without private information. Potential instruments for private information in such settings could include: number and depth of past interactions between salesperson and customer, salesperson tenure, demographic similarities between salesperson and customer).

[6] In the model, we normalize salary to 1 and model the salesperson's behavior to earn B_{jt} only, because (i) we do not observe all salespeople's salary in all periods, and (ii) there is little variation in salary across salespeople (coefficient of variation: 5.5%).

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

Maintenance performance is measured using a maintenance index $M_{jt} = g(R_{jt}/O_{jt})$, where R_{jt} is the amount of repaid loans, O_{jt} is the outstanding value and $g(\cdot)$ is an increasing function of R_{jt}/O_{jt}, The details of the $g(\cdot)$ function are in Appendix. The overall bonus compensation is a product of the two indices: $B_{jt} = A_{jt} \times M_{jt}$. Since the bonus is bounded below by zero and is incremental to salary, salespeople have limited liability.

4.3. Actions

The salesperson's set of actions depends on whether she has private information (i.e., whether she is in the learning period or not). With private information, the salesperson knows the unobservable loan types and can hence choose four levels of effort: acquisition effort for good and bad loan types, denoted as $e_{jt}^{A_G}$ and $e_{jt}^{A_B}$, and maintenance effort for good and bad loan types, which are denoted as $e_{jt}^{M_G}$ and $e_{jt}^{M_B}$.

In contrast, without private information, the salesperson cannot distinguish loan types and therefore can only choose total acquisition effort e_{jt}^{A} and total maintenance effort e_{jt}^{M} with the expectation that the effort will be allocated to good and bad loan types in proportion to their population share. We assume that the population share of loan types in each branch/period is common knowledge, and salespeople make their effort allocations based on this common information. In other words, letting p_{jt}^{G} be the probability of a loan being a good loan in the branch at which salesperson j works at time t, the acquisition and maintenance efforts, e_{jt}^{A} and e_{jt}^{M}, are allocated to good loans with probability p_{jt}^{G} and to bad loans with probability $1 - p_{jt}^{G}$.

4.4. State Variables

For a salesperson *without* private information, the state variables s_{jt}^{A} that determine acquisition effort e_{jt}^{A} include the amount of outstanding loans O_{jt}, the amount of loans that would expire at the end of period E_{jt}, acquisition quota Q_{jt}, and salesperson tenure τ_{jt}. O_{jt} and E_{jt} as well as the amount of loans acquired in period t determine the portfolio size that the salesperson j needs to collect from *in the next period* as we will discuss in Section 4.6. Acquisition quota Q_{jt} directly affects e_{jt}^{A} through the acquisition index. We include τ_{jt} as a state variable to proxy salesperson j's ability and knowledge.

Similarly, maintenance effort e_{jt}^M is affected by the amount of outstanding loans, the lagged amount of repaid loans R_{jt-1}, and tenure. The amount of repaid loans in period $t-1$ (R_{jt-1}) provides information on the repayment likelihood of existing loans, and thus impact the maintenance pressure on salesperson j. The amount of loans that expires at the end of period E_{jt} does not matter in maintenance effort decision, which takes into account the portfolio size in the current period only.

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

Finally, state variables for maintenance efforts for type ω loans, $s_{jt}^{M_\omega}$ ($\omega \in \{B, G\}$), include the outstanding loan amount of type ω, O_{jt}^ω, the lagged amount of repaid type ω loans $R_{j,t-1}^\omega$, and tenure. Table 4 summarizes the state variables for each action.

Table 4   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_{jt-1})		Endogenous	Outstanding - Good, Bad (O_{jt}^G, O_{jt}^B), Lagged Repaid - Good (R_{jt-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_{jt-1}^B),
				Exogenous	Tenure (τ_{jt})

4.5. Salesperson Production Functions

Following Misra and Nair (2011) and Chung et al. (2013), we model the salesperson's outcomes as production functions arising from three components: (1) her effort policy

functions; (2) exogenous production shifters and (3) idiosyncratic production shocks not known to the salesperson when choosing efforts. The key differences with respect to the prior research in addressing multidimensional performance with private information are as follows: (1) we accommodate multiple dimensions of outcomes (acquisition and maintenance); (2) we allow for private information in terms of good and bad loan outcomes; this also implies that effort choice will also include acquisition and maintenance effort on good and bad loans and (3) we allow for correlation in the shocks across the outcome equations.

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

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

where $e_{jt}^{A_G}(\cdot; \lambda^{A_G})$ and $e_{jt}^{A_G}(\cdot; \lambda^{A_B})$ are the continuous acquisition effort policy function for good and bad loans respectively, $f(\cdot; \beta^{A_G})$ and $f(\cdot; \beta^{A_B})$ are the effects of exogenous shifters (X_{jt}), and $\epsilon_{jt}^{A_G}$ and $\epsilon_{jt}^{A_B}$ are idiosyncratic shocks such as unexpected market condition in each market/period that are neither anticipated nor observed by salesperson j before the effort choices. Finally, λ^{A_ω} and β^{A_ω} ($\omega \in G, B$) are the parameters to be estimated. We will explain the variables included in X_{jt} in Section 5.

Note that the acquisition effort policy function for good loans depend on both the state variables associated with other tasks $s_{jt}^{\backslash A_G}$ as well as the state variables associated with acquiring good loans $s_{jt}^{A_G}$. $e_{jt}^{A_G}$ is affected by $s_{jt}^{\backslash A_G}$ because acquisition and maintenance efforts are jointly chosen. Hence, outcomes are determined by all state variables through effort choices for other actions. Note also that when the salesperson does not have private information, the allocation of efforts across loan types is out of the salesperson's control and determined by the fraction of good and bad type loans in population.[7]

---

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

$$
\begin{aligned}
N_{jt}^G &= p_{jt}^G e_{jt}^A(s_{jt}^A, s_{jt}^{\backslash A}; \lambda^{A_G}) + f(X_{jt}; \beta^A) + \epsilon_{jt}^{A_G}, \\
N_{jt}^B &= (1 - p_{jt}^G) e_{jt}^A(s_{jt}^A, s_{jt}^{\backslash A}; \lambda^{A_B}) + f(X_{jt}; \beta^A) + \epsilon_{jt}^{A_B},
\end{aligned}
$$

where p_{jt}^G is the fraction of good loans in the population, which can vary by salesperson j's branch.

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

$$
\begin{aligned}
R_{jt}^G &= e_{jt}^{M_G}(s_{jt}^{M_G}, s_{jt}^{\backslash M_G}; \lambda^{M_G}) + h(X_{jt}; \beta^{M_G}) + \epsilon_{jt}^{M_G}, \\
R_{jt}^B &= e_{jt}^{M_B}(s_{jt}^{M_B}, s_{jt}^{\backslash M_B}; \lambda^{M_B}) + h(X_{jt}; \beta^{M_B}) + \epsilon_{jt}^{M_B},
\end{aligned}
\tag{2}
$$

where $e_{jt}^{M_G}(\cdot; \lambda^{M_G})$ and $e_{jt}^{M_G}(\cdot; \lambda^{M_B})$ are the continuous maintenance effort policy function for good and bad loans respectively $h(\cdot; \beta^{M_G})$ and $h(\cdot; \beta^{M_B})$ are the effects through exogenous shifters X_{jt}, and $\epsilon_{jt}^{M_G}$ and $\epsilon_{jt}^{M_B}$ are idiosyncratic shocks. λ^{M_ω} and β^{M_ω} ($\omega \in G, B$) are the parameters to be estimated.

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

4.6. State Transitions

Among the state variables in Table 4, tenure increases by one every period, i.e., $\tau_{jt+1} = \tau_{jt} + 1$. All the other state variables in period $t+1$ are reset and exogenously given as j gets transferred to a new branch at the beginning of $t+1$. In other words, a transferred salesperson's amount of outstanding, to-be-expired and lagged repaid loans in the portfolio; and the acquisition quota are exogenously determined, having nothing to do with her states in the previous branch in period t before transfer.

Here, we mainly discuss the state transitions when j is not transferred at the beginning of $t+1$. First, if the states are not distinguished by type, the states in period $t+1$ evolve from those in period t regardless of presence of private information. Total outstanding amount follows the deterministic transition:

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

where N_{jt} is the amount of acquired loans by salesperson j in period t and E_{jt} is the amount of j's loans to be expired at the end of period t. Acquisition quota Q_{jt+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 $t+1$, although the exact formula is

not known to us. We model the relationship between the explanatory variables and the acquisition quota in period $t+1$ using a flexible parametric function with parameters ϕ as follows:

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

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

More importantly, the evolution of j's state variables *distinguished by type* depends on the presence of private information in period t. If j is in the learning period in time t (i.e., salesperson j does not have private information in period t but has it in $t+1$), j's states by type are not observed in t, but observed in period $t+1$. The amounts of outstanding, to-be-expired and lagged repaid loans *of each type* in period $t+1$ ($O_{jt+1}^w, E_{jt+1}^w, R_{jt}^w$ where $w \in \{G, B\}$) are exogenously determined at the beginning of $t+1$ based on the learnt private information. If period t is *after* the learning period (i.e., salesperson j has private information in both periods t and $t+1$), the amounts of outstanding loans by type evolve deterministically as follows:

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

4.7. Flow Utility Function

A salesperson's flow utility is determined by her bonus given state variables and effort minus the cost of effort. Salesperson j earns bonus $B(N_{jt}, R_{jt})$ based on acquisition and maintenance performance outcomes, where $N_{jt} = N_{jt}^G + N_{jt}^B$ and $R_{jt} = R_{jt}^G + R_{jt}^B$ and incurs cost $C(e_{jt})$, where $e_{jt} = \left\{ e_{jt}^{A_G}, e_{jt}^{A_B}, e_{jt}^{M_G}, e_{jt}^{M_B} \right\}$ if the salesperson has private information and $e_{jt} = \left\{ e_{jt}^A, e_{jt}^M \right\}$ otherwise. The utility function for period t is defined by the following:

$$U(e_{jt}, N_{jt}, R_{jt}; \Theta_j) = B(N_{jt}, R_{jt}) - C(e_{jt}; \Theta_j), \tag{4}$$

where the bonus is computed following the firm's compensation plan as $B(N_{jt}, R_{jt}) = \left(\frac{N_{jt}}{Q_{jt}} \right) * g\left(\frac{R_{jt}}{O_{jt}} \right)$. Here, $\frac{N_{jt}}{Q_{jt}}$ denotes Acquisition index, and $g\left(\frac{R_{jt}}{O_{jt}} \right)$ is Maintenance index, where $g(.)$ is a function that maps maintenance performance to maintenance points as in Table A1. Note that the salesperson is not risk averse, but the bank cannot assign all risk to the salesperson due to limited liability. Therefore the firm still has to address the moral hazard problem.

We specify the effort cost function for the salesperson with private information as follows.

$$C(e_{jt};\Theta) = \theta^C \left[\underbrace{(e_{jt}^{A_G} + \theta^{A_B} e_{jt}^{A_B})}_{\text{Acquisition cost}} + \theta^M \underbrace{(e_{jt}^{M_G} + \theta^{M_B} e_{jt}^{M_B})}_{\text{Maintenance cost}} \right]^2, \tag{5}$$

where θ^C measures the relative magnitude of effort to (monetary) bonus, θ^{A_B} is the parameter for acquiring bad loans relative to good loans, θ^M is the parameter for maintenance effort relative to acquisition effort, θ^{M_B} is the parameter for maintaining bad loans relative to good loans. Note that if θ^M is greater than 1, monitoring effort is costlier than acquisition effort. We denote $\Theta = \{\theta^C, \theta^{A_B}, \theta^M, \theta^{M_B}\}$, on which we do not impose any restrictions.

4.8. Bellman Equation

A salesperson makes effort decisions in a dynamically optimal manner so that she maximizes the expected discounted sum of utility given state variables S_{jt}; state transition parameters ϕ; policy function parameters β and λ; j's belief in 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. Her Bellman equation can be written as:

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

where δ is a monthly discount factor, which we assume to be 0.99,[8] and S' is the state variables for the next period. The expectation is obtained with respect to the idiosyncratic shocks in each period, the probability of being transferred, and the transition from one month learning period to the post-learning periods.

4.9. Model Discussion

As we discussed in the introduction, one of our goals in the paper is to develop a workhorse modeling and estimation framework for the structural analysis of a multitasking salesforce. The rich empirical setting requires us to incorporate several features into the model, but special cases or minor adaptations can be applied to a range of other settings.

First, our model accommodates private information, but special cases of our model can be used in multitasking salesforce settings *without* private information. The effort

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[8] Since this is an infinite horizon setting with only monthly bonuses and no annual bonuses, we use the common approach of assuming discount factors as in Misra and Nair (2011). This is in contrast to Chung et al. (2013), who are able to estimate discount factors by exploiting the finite horizon bonus scheme in their empirical setting.

allocation feature across multiple tasks will continue to be relevant in settings without private information.

Second, our empirical setting requires a dynamic structural model with forward-looking behavior salespeople because of the intertemporal linkages between acquisition and repayment. In setting without such intertemporal linkages, a simpler static model of multitasking can be used. For example, when compensation is based on two dimensions without intertemporal linkages (e.g., sales quantity, and customer satisfaction with sales activities), a simpler static model would be sufficient.

Finally, in our setting, given observable and exogenous random transfers, we model the absence or presence of private information deterministically during and after a learning period. In settings, where such a feature to proxy for private information may not be available, researchers can consider instruments that are exogenously related to private information, and model private information as probabilistic. Footnote 5 elaborates this.

5. Estimation and Identification

We estimate the model using two-step forward-simulation based estimation (Bajari et al. 2007). In the first step, we estimate the salesperson's production function, which includes the salesperson's (nonparametric) effort policy functions, with flexible mappings between states, actions, and performance outcomes. These first-stage effort policy functions are assumed to reflect the optimal actions of the salesperson, given the observable state variables. In the second step, we estimate the structural parameters that rationalize the estimated effort policy functions of the first step as optimal. We use moment inequality based estimation for the second step, where the inequalities are constructed based on the idea that deviations in effort from the estimated effort policy functions should have lower payoffs for the salesperson, given that these policies are assumed optimal.

We allow salespeople to be heterogeneous in their cost of customer acquisition and maintenance. As in Chung et al. (2013), we use an EM-type algorithm by Arcidiacono and Miller (2011) to accommodate unobserved salesperson heterogeneity and obtain the heterogeneous effort policy functions with the probability that each salesperson belongs to one of the (latent) discrete segments in the first step. We then estimate the structural parameters in the second stage by segment.

There are two further challenges in estimating the model. First, with multitasking (and four outcomes in our application), there are many more state variables compared to single-task settings, whose relationship with the outcome variables need to be nonparametrically estimated. Semiparametric/nonparametric estimation typically faces a severe curse-of-dimensionality problem when there are many variables. We, therefore, use a machine learning method for the high-dimensional nonparametric estimation. Specifically, we use Random Forest with cross-fitting (to avoid over-fitting) to estimate the first-stage policy functions.

Second, a salesperson with private information makes separate effort decisions for *ex ante* good and bad loans. However, the loan type (*ex ante* profitability) conditional on public information is not directly observed by researchers. Hence, we need to infer the loan type from observed *ex post* realized profitability, controlling for the influence of the salesperson's behavior and other exogenous factors. We embed the inference of unobservable loan types as another iterative step similar to estimating the heterogeneous latent segments.

Figure 5 provides an overview of the steps involved in implementing the two-stage estimation procedure for our application. We explain each of these steps in the following sub-sections. The first stage estimation is an iterative procedure over Step 1a (for inference of loan types) and Step 1b (inference of production functions for heterogeneous segments) until both the loan type classification and the salesperson type segmentation converge. In the second stage of the estimation, the structural parameters are estimated in Step 2.

5.1. Step 1a: Loan Type Inference

In this step, we infer loan type (i.e., *ex ante* loan profitability) from *ex post* loan profitability, or realized Internal Rate of Return (IRR). Since the salesperson can affect *ex post* loan profitability through the loan cycle, the *ex ante* profitability is not directly observed. Hence, the inference of *ex ante* loan type requires us to filter out 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). We do so in the following steps.

5.1.1. Mapping between observables and loan profitability. We first model the ex-post IRR of loan i (IRR_i), as a flexible function of observable and unobservable characteristics as follows:

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

Figure 5   Estimation Overview
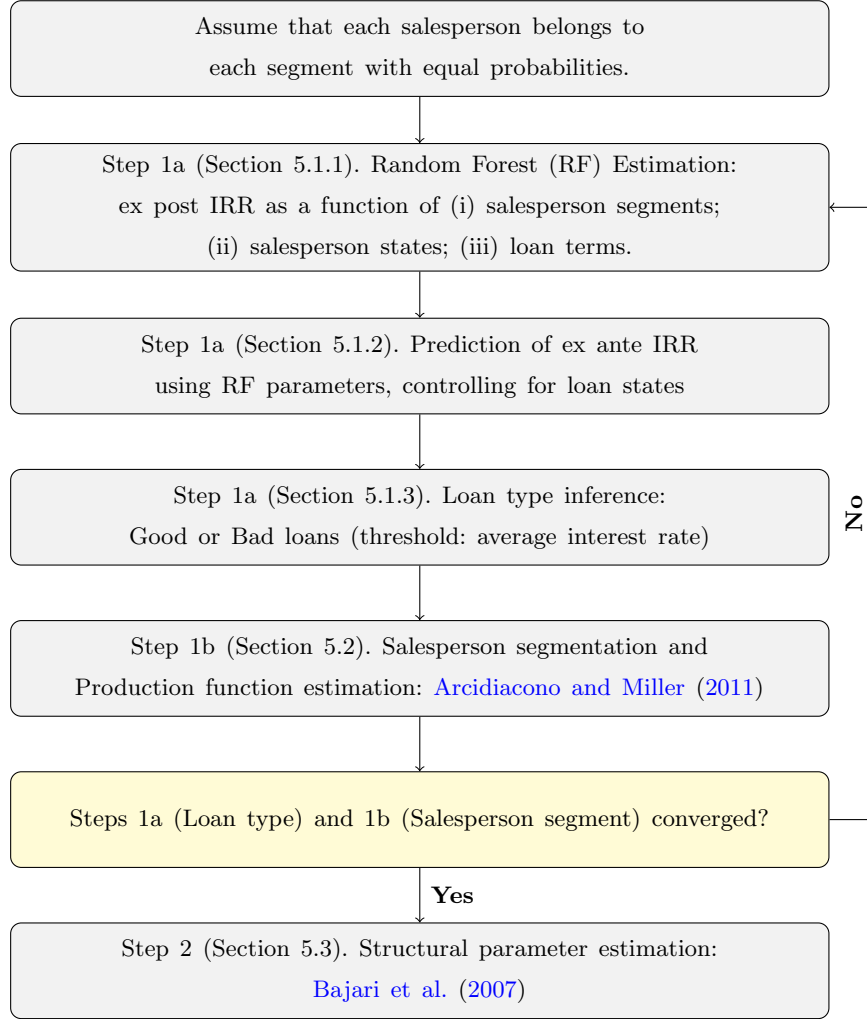
where L_i is the vector of loan/borrower characteristics of loan i, $K_{j(i)}$ is the latent segment of salesperson j who acquires loan i, and $State_{j(i)t...T(i)}$ includes salesperson characteristics and compensation states during the loan cycle, from the acquisition period t until the maturity T. We provide the summary statistics of these explanatory variables in the online appendix. The random forest algorithm allows us to estimate the flexible function $f(.)$, without making ad-hoc assumptions on the functional form of $f(.)$.

There are two empirical challenges in estimating equation (7): unobservability of salesperson segment $K_{j(i)}$ and potential endogeneity of $State_{j(i)t...T(i)}$. First, $K_{j(i)}$ is not directly observed in the data. We therefore iterate on the loan classification step (Step 1a) taking segment classification as given from the previous step and the heterogeneous (segment-

wise) policy function estimation step (Step 1b) based on the loan classification from the previous step until both steps converge.

Second, although salesperson characteristics and time-varying compensation states $State_{j(i)t...T(i)}$ are observed in the data, unobserved factors (e.g., loan type) may affect both $State_{j(i)t...T(i)}$ and IRR_i in equation (7), which may bias our inference of *ex ante* loan profitability. To handle this endogeneity issue, we instrument $State_{j(i)t...T(i)}$ with $Z_{j(i)t...T(i)}$, which affect salesperson compensation states, but do not affect the return of loan i. The instruments include (i) salesperson j's transfer status, (ii) the average IRR of the other loans acquired by salesperson j in period t, and (iii) the average IRR of other loans maintained by salesperson j in period t. Such variables affect the compensation states because they are determined by the *aggregate* profitability of loans in j's portfolio, but does not directly affect IRR_i, which is solely determined by loan i's profitability conditional on observables.

To implement the 2SLS-like estimation, we first regress the compensation state variables, $State_{j(i)t...T(i)}$, on the instruments, $Z_{j(i)t...T(i)}$, and then plug the predicted value $\hat{State}_{j(i)t...T(i)}$ into equation (7) to estimate $f(.)$ with Random Forest.[9] When training the random forest algorithm, we make use of the information from 60,970 loans, for which there are no missing predictors. We hold out 30% of the observations for the test data and find that 1,000 trees with 15 predictors give the best prediction with the lowest mean square error for the test data. We report the importance of each variable in the online appendix.

5.1.2.   Predicting *ex ante* IRR. Using the estimated Random Forest model, we predict *ex ante* profitability of loans, controlling for salesperson factors. The salesperson factors include salesperson segment $K_{j(i)}$ and her characteristics/states $State_{j(i)t...T(i)}$ (e.g., how many loans to be collected by j on average from period t to T, what fraction of j's existing loans are being repaid on average from period t to T). The last variable shifts the salesperson's maintenance behaviors during the cycle of loan i and eventually affects *ex post* IRR of loan i. Specifically, we predict the *ex ante* IRR ($\hat{IRR}_i$) as follows,

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

[9] Although this 2SLS-type approach allows a non-parametric function for $f()$, a caveat is that the asymptotic properties of the predicted value of $f()$ are not well-established in the literature (Athey et al. 2017). We check the distribution of the prediction errors, which is centered close to zero.

where $\tilde{K}_{j(i)}$ is the fixed effect for salesperson segment and $\tilde{State}_{j(i)t...T(i)}$ is the average compensation states of salesperson j across all loans/periods. We control for the segment fixed effect in the iterative process between Step 1a and Step 1b.[10]

To predict *ex ante* loan profitability, we set $State_{j(i)t...T(i)}$ at the average compensation states of salesperson j. The idea is that the the effect of the salesperson's state on loan collection (and IRR) would be the least when they are in their average state—and thus reflect the true ex ante IRR.[11]

5.1.3.   **Classification of Loans.** Given the predicted *ex-ante* profitability, we classify a loan into a good loan (i.e., a profitable, but harder-to-acquire loan) if $I\hat{R}R$ is greater than a threshold level (average interest rate of all loans i.e., 87.5% yearly interest rate) and a bad loan (i.e., an unprofitable, but easier-to-acquire loan) otherwise. Based on this classification rule, good loans account for 57% of the loans in the data.[12]

After classifying each loan into either good or bad type, we aggregate the amount of acquired or repaid loans by loan type, for each salesperson in each period to create four outcome variables: 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).

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

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

$$
\begin{aligned}
N_{jt}^\omega &= e_{jt}^{A_\omega}(S_{jt}; \lambda^{A_\omega}) + f(X_{jt}; \beta^{A_\omega}) + \epsilon_{jt}^{A_\omega}, \\
R_{jt}^\omega &= e_{jt}^{M_\omega}(S_{jt}; \lambda^{M_\omega}) + h(X_{jt}; \beta^{M_\omega}) + \epsilon_{jt}^{M_\omega},
\end{aligned}
\tag{8}
$$

where $\omega \in \{G, B\}$. Salesperson with private information (those not in the learning period) makes the four-dimensional effort choice. However, those within the learning period make

---

[10] After we compute $I\hat{R}R_i$ of the 60,970 loans, we match the remaining 39,280 loans, that had some missing predictors, to one of the 60,970 loans in the model by propensity score matching. The matching is based on loan characteristics and salesperson characteristics/states, and weighted by the variable importance (reported in online appendix).

[11] We assessed sensitivity to the assumption by setting $\tilde{State}_{j(i)}$ to (i) average compensation states across all salespeople/loans/periods and (ii) zero. The ex-ante IRR is insenstive to these alterative assumptions, suggesting that this has little weight in predicting ex ante IRR. More details are in the online appendix.

[12] Our results are robust to the loan classification rule. For example, when we based the threshold of good and bad loans on the branch-level average interest rate, 55% of loans are classified as good.

only two-dimensional effort choice for total acquisition and total maintenance. The allocation of efforts across loan types is determined by the population distribution of good and bad loans. As discussed above, since a multitasking salesperson makes acquisition and maintenance decisions, each effort function can be written as a function of all state variables as follows:[13]

$$e_{jt}^{T_\omega}(S_{jt}) \equiv e_{jt}^{T_\omega}(s_{jt}^{A_G}, s_{jt}^{A_B}, s_{jt}^{M_G}, s_{jt}^{M_B}),$$

where $T \in \{A, M\}$ denotes either acquisition or maintenance and $\omega \in \{G, B\}$ denotes loan type. We allow the effort policy functions to be nonparametric and estimate them with the random forest method. An alternative way to estimate the policy function is to use the Chevyshev polynomial approximation as used by the previous papers such as Chung et al. (2013). In the Chevyshev polynomial approximation method, the researchers need to choose the number of orders for the basis functions and the set of variables for each of the basis functions. Given a large number of state variables, it is not straightforward to do so. By contrast, a benefit of using Random Forest in the first stage is that we do not need to determine those in an ad-hoc way.

In equation (8), the exogenous shifters X_{jt} include branch-level average acquisition quota $\overline{Q}_t^b$; and the interaction between τ_{jt} and $\overline{Q}_t^b$. The main effect of salesperson tenure τ_{jt} is captured in the effort decision. The salesperson's 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.[14] We specify $f(\cdot)$ (and $h(\cdot)$) as a linear function, i.e., $f(X_{jt}; \beta^{T_\omega}) = X_{jt}' \beta^{T_\omega}$. Lastly, the four-dimensional shocks $(\epsilon_{jt}^{A_G}, \epsilon_{jt}^{A_B}, \epsilon_{jt}^{M_G}, \epsilon_{jt}^{M_B})$ follow a multivariate normal distribution with mean 0 and covariance matrix Σ. We allow shocks to be correlated with one another for the same salesperson in the same period, but i.i.d across salespeople or across periods.

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

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[13] We do not explicitly model the limited total time/resource allocated by salesperson j among multiple tasks, because all salespeople do not spend an equal amount of time at work. Yet, modeling that acquisition and maintenance efforts affect each other handles account for the effort allocation across tasks.

[14] The results are robust to inclusion of period dummies (that can account for potential seasonality) and main effect of tenure in X_{jt}. Details are in the online appendix.

heterogeneity through persistent latent segments and estimate heterogeneous policy functions using the EM algorithm developed in Arcidiacono and Miller (2011), and empirically applied in Chung et al. (2013). A latent segment is denoted by $k \in \{1, 2, ..., K\}$ (K is the number of discrete segments) and we estimate segment-level efforts $(e_k^{A_G}, e_k^{A_B}, e_k^{M_G}, e_k^{M_B})$ and a covariance matrix Σ_k in this step. More details of the semiparametric estimation and EM algorithm are provided in the appendix.

Combining Step 1a and Step 1b As Figure 5 describes, we iterate between the loan type inference step (Step 1a) and the heterogeneous production function estimation step (Step 1b) until convergence. Since loan types and latent segments are both unobserved in the data, we have to iteratively execute Step 1a and Step 1b, starting from the initial guess of the latent segment distribution (i.e., 50% for each segment). Given the estimates of the loan types obtained in Step 1a, we estimate the latent segment distribution in Step 1b. We iterate on these steps till both the loan type and the salesforce latent segment distribution converge. The iterative procedure enables us to jointly estimate loan type and salesperson segment, and to control for salesperson segment $K_{j(i)}$ in the loan type inference.

5.3.   Step 2: Structural Parameter Estimation

In the second step, we estimate the structural parameters Θ_k, consisting of the parameters related to the total effort (θ_k), the acquisition effort for bad loans relative to good loans ($\theta_k^{A_B}$), the maintenance effort relative to acquisition effort (θ_k^M), and the maintenance effort for bad loans relative to good loans ($\theta_k^{M_B}$) for each salesperson segment k. Our estimation strategy follows the forward-simulation approach in Bajari et al. (2007). Hence, we first recover the value function under the optimal policy (the estimated effort policy function), denoted by $\hat{V}$, and then calculate the counterfactual value function under the policies that deviate from the optimal policy, denote by $\tilde{V}$.[15] Lastly, the moment inequalities can be constructed from the difference between two value functions. Segment-level structural parameters are estimated by the minimum distance estimator of the difference between $\tilde{V}(s|k; \tilde{e}_k, \hat{\beta}_k, \hat{\Sigma}_k, \phi, \Theta_k)$ and $\hat{V}(s|k; e_k, \hat{\beta}_k, \hat{\Sigma}_k, \phi, \Theta_k)$ for each segment:

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

---

[15] The reported results are based on adding a random normal shock with standard deviation of 0.01 to the optimal strategy. They remain robust to deviations of random normal shocks with standard deviation of 0.1. We forward-simulate over 14 periods and average over 100 simulations to calculate $\hat{V}$. More details are in the online appendix.

where e_k is the estimated optimal policy and $\tilde{e}_k$ is the deviated policy.

Following Bajari et al. (2007), we estimate standard errors based on 500 randomly selected bootstrapped samples. To take into account the estimation error in the first stage, we estimate both the first stage and the second stage for each bootstrapped sample. However, since we use the Random Forest algorithm in the first stage policy estimation, this simple bootstrapping may not be enough to correctly estimate standard errors. Although there are a few recent papers that show how to correct standard errors in the two-step estimation such as Chernozhukov et al. (2019) and Chernozhukov et al. (2018b), it is still hard to apply the methods to complicated dynamic structural models with continuous choice variables like ours. Hence, our standard errors estimates may be biased to the extent of the necessary adjustments developed in these recent papers. In the online appendix, we conduct a sensitivity analysis on this issue by changing the degree of perturbation.

5.4. Identification

We now discuss the identification of the multitasking model with private information. It is useful to begin with the dynamic structural models for single task salesforces with unidimensional incentives (e.g., Misra and Nair 2011, Chung et al. 2013) and assess how we handle identification challenges arising from the new features (i) multitasking with multidimensional incentives and (ii) private information. For ease of exposition, we begin with the extension to multitasking with multidimensional incentives, ignoring the issue of private information. Then we discuss the additional identification issues related to private information.

5.4.1. Multitasking with multidimensional incentives. It is critical for the identification of the multitasking model to observe performance outcomes related to each task or each dimension that is incentivized. Beyond that, most of the identification assumptions for the multitasking model follow the single task papers. First, the assumptions are about the links between effort and outcomes. To the extent that we observe acquisition outcomes and retention outcomes (linked to the two tasks), we assume (i) outcomes are a strictly monotonic function of each effort; (ii) outcomes are an additively separable function of production shifters, effort, and production shocks; and (iii) since effort is not observed, the multiplier effect of effort on the outcome is normalized to 1.

The fourth assumption that is needed for the identification of $e(\cdot)$, $f(\cdot)$, and $h(\cdot)$, is the orthogonality condition for the error, i.e., $E[\epsilon|S, X] = 0$, where S is the vector of the salespeople's state variables, and X is the vector of exogenous demand shifters. Behaviorally, this implies that the effort function $e(S)$ is a deterministic function of S, and $f(\cdot)$ and $h(\cdot)$ are deterministic functions of X_{jt}. In other words, there's no unobserved heterogeneity in outcomes conditional on the state variables (including the latent class of salespeople) and the exogenous shifters. In addition, the multitasking model requires us to identify covariance in multitask outcomes. The covariance in outcomes N_{jt} and R_{jt} conditional on states S_{jt} and exogenous shifters X_{jt} allows us to identify the covariance of shocks Σ.

The structural parameters in the effort cost function, Θ, are identified from the intertemporal linkage of states, efforts, and outcomes. More specifically, given the outcome functions identified and our assumption on the utility function from the bonus, the optimality condition of the salesperson's efforts choice problem pins down the effort cost parameters.

As in Chung et al. (2013), the identification of unobserved finite mixture heterogeneity follows Kasahara and Shimotsu (2009), which show that at least three periods of panel data is necessary for the identification. We note that unlike their discrete choice model, ours is a continuous choice model. However, our loan-officer panel data is significantly longer (than three periods) and therefore would be sufficient for identification.

Thus to summarize, the identification requirements for extending single-task models to the multitask model with multidimensional incentives are straightforward. The model is identified if we have a performance metric for each task or performance dimension.

5.4.2. Private Information. Next, we consider the identification of the model with private information. In our setting, the salesperson's private information is the knowledge of which loans are good or bad conditional on observables so that the salesperson can optimally exert the right level of effort on good and bad loans. Identification of the model with private information is achieved by the ability to infer the type of loans from the ex-post realization of loan repayment, i.e., the ex-post IRR of the loan is necessary for us to classify the good and bad loans. Given this information (similar to the arguments for the model without private information), researchers can infer what effort was made on not just acquisition and maintenance in each period, but also on good and bad loans in each period. And as such, it is possible to identify all the structural parameters of the model—the cost of effort in acquiring and maintaining good and bad loans.

Note that the above identification argument did not place any role for transfers that we observe in the data. We now clarify the role of transfers in estimating the model. Without transfers, all periods in the data have private information. However, with transfers, there is a learning period in which salespeople do not have private information. In the learning period, we make the structural assumption that salespeople cannot allocate effort based on loan type—they simply decide on how much effort to allocate to acquisition and maintenance, and the effort on good and bad loans are allocated based on the distribution of loan types in the population. Indeed, as we report in Table A2 in the appendix, salesperson behavior in the learning period is different from the other periods. Thus modeling behavior after transfer involves only a structural assumption —there are no new structural parameters to estimate. Hence while transfers provide over-identifying restrictions in the model, they are not necessary for identification of the structural parameters.

6. Results

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

6.1. First Stage Estimates: Loan officer production functions

Table 5   Loan Officer Outcome Functions: Demand Shifters

	Segment 1	Segment 2
Segment Share	68 %	32 %
Acquisition of Good Loans		
Average Quota (branch)	44.68 (0.170)	38.15 (0.096)
Tenure * Average Quota (branch)	-10.44 (0.040)	-9.27 (0.022)
Intercept	-6.81 (0.033)	-6.92 (0.033)
Acquisition of Bad Loans		
Average Quota (branch)	11.94 (0.053)	9.38 (0.042)
Tenure * Average Quota (branch)	4.32 (0.016)	4.91 (0.014)
Intercept	-8.55 (0.036)	-6.22 (0.031)
Maintenance of Good Loans		
Average Quota (branch)	-1.28 (0.004)	-0.45 (0.011)
Tenure * Average Quota (branch)	1.44 (0.005)	1.17 (0.004)
Intercept	-1.78 (0.007)	-1.57 (0.005)
Maintenance of Bad Loans		
Average Quota (branch)	-33.04 (0.138)	-33.21 (0.071)
Tenure * Average Quota (branch)	0.92 (0.004)	0.95 (0.003)
Intercept	3.07 (0.013)	3.07 (0.008)

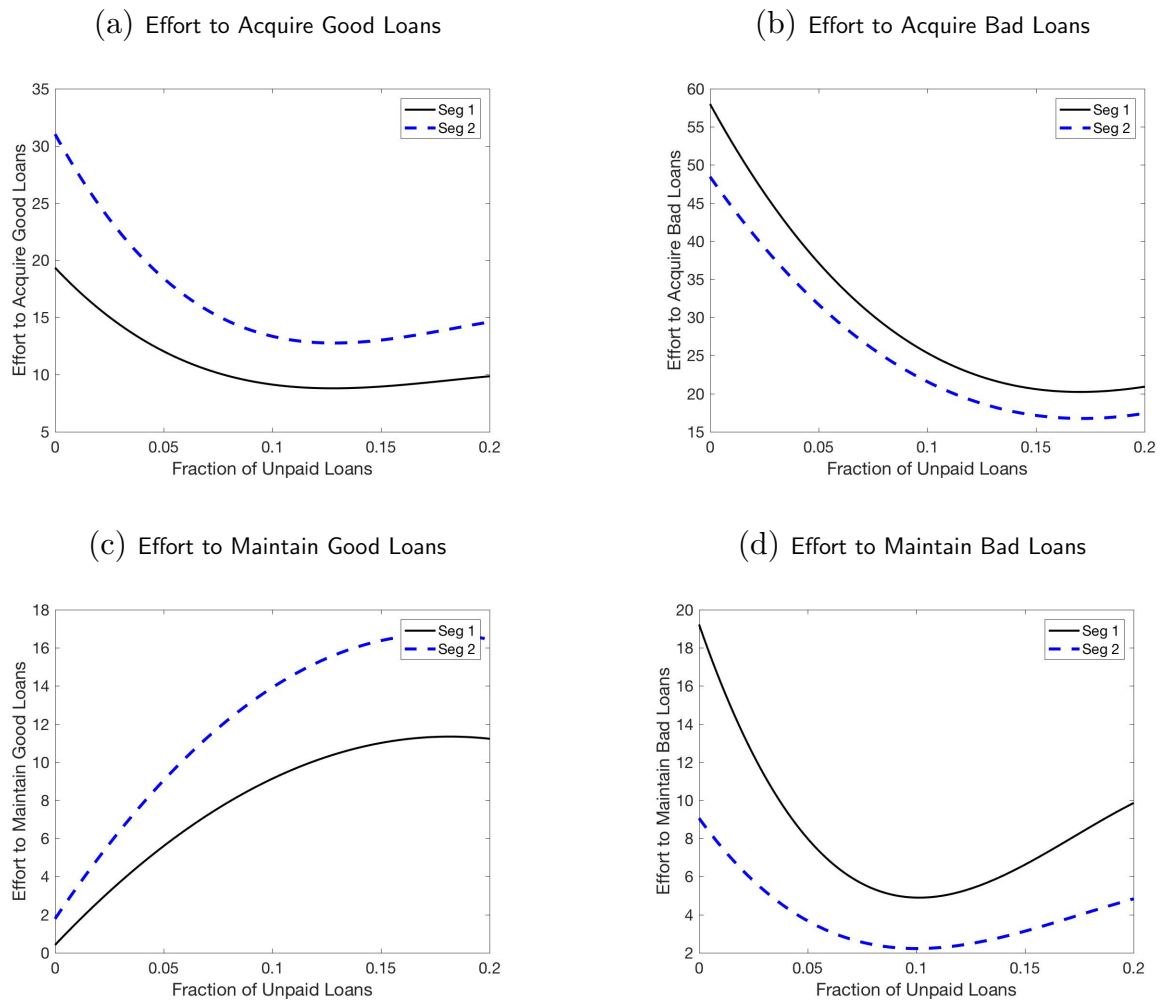Note: Standard errors are in the parentheses.

In the first stage, we allow discrete latent segments in the loan officer production functions, and find that a two segment model—one with a segment share of 68% and other with 32%, best fits the data. We then estimate the loan production functions for each segment and report the estimates of the exogenous production shifters for each type of outcomes by segment in Table 5. The first two panels show the impact of exogenous shifters on acquisition performance for good loans and bad loans respectively. Not surprisingly, acquisitions are greater in branches with higher quotas, reflecting their greater market size. Interestingly, experience (tenure) reduces the incremental impact on good loans; however, it increases the incremental impact of bad loans, suggesting that experienced salespeople are better at using private information to acquire bad loans at the margin.

The bottom two panels of the table present the estimates for maintenance performance functions for good and bad loans respectively. The results imply that as the average acquisition quota increases, repayment performance deteriorates. This is understandable as salespeople must exert more effort in loan acquisition when there are larger quotas and thus focus less on loan collection. As expected, experience helps salespeople to improve maintenance.

Next, we report some illustrative features of the high-dimensional nonparametric acquisition and maintenance effort policy functions. Figure 6 shows the four types of effort by segment against the *fraction of unpaid loans in period* $t-1$–a proxy of the quality of the loan portfolio of the officer—a relevant state variable. Note that the higher the fraction of unpaid loans, the lower the quality of the current loan portfolio, and the more difficult it is to perform well on the maintenance metric. The first and second subplots in Figure 6 show the *acquisition effort* on good and bad loans, respectively, while the third and fourth subplots show the corresponding *maintenance effort*.

A few aspects stand out from the plots. First, Segment 2 loan officers expend more effort on good loans relative to Segment 1, whereas Segment 1 expends more effort than Segment 2 on bad loans. This suggests that the moral hazard issues are greater with Segment 1 than with Segment 2. Second, both segments exert more acquisition effort when the quality of the loan portfolio is good; but they reduce acquisition effort and increase maintenance effort when the portfolio quality is bad, as seen in the maintenance plots. Third, the maintenance effort on bad loans increases when the fraction of unpaid loans is higher than 0.1. This reflects the highly nonlinear compensation schedule, where the maintenance index (M)

Figure 6   Effort Policy by Segment depending on Fraction of Unpaid Loans in the Previous Period

(a) Effort to Acquire Good Loans

(b) Effort to Acquire Bad Loans

(c) Effort to Maintain Good Loans

(d) Effort to Maintain Bad Loans

drops sharply to zero at approximately 12.5%; incentivizing salespeople to redirect more effort more to maintenance.

6.2. Cost Parameter Estimates

Table 6 reports the estimates of the structural parameters in the effort cost functions.[16] As indicated by the higher θ_k^C, Segment 2 has greater disutility for effort than Segment 1; thus, Segment 1 is overall more productive. The estimate $\theta_k^{A_B}$, shows that for Segment 1, the acquisition effort for bad loans is only about 15% of the acquisition effort for a good loan. This is in contrast to Segment 2, for whom the relative cost for acquiring a bad loan is around 97% of that for the good loan. Thus, although Segment 1 is overall more productive, there is also a greater danger of moral hazard from Segment 1 in using private information to acquire more bad loans.

In terms of the maintenance cost, the estimate of θ_k^M shows that Segment 1's cost of maintenance effort is about the same as that for acquisition. Also, from $\theta_k^{M_B}$, we see the cost of maintaining bad loans and good loans are roughly equal. In contrast, Segment 2 find the cost of maintenance of good loans only 30% of the cost of acquisition, but find the cost of maintenance of bad loans three times more difficult. Thus overall, Segment 2 is less likely to acquire bad loans and is also more effective in collecting the good loans it acquires. However, given its high overall cost, it will acquire overall fewer loans.

Based on these estimates, we label Segment 1 as the "hunter" segment and Segment 2 as the "farmer" segment. The hunter segment is not only relatively good at acquiring new customers, but also likely to acquire more bad customers. The "farmer" segment has a comparative advantage in collecting past loans (especially good loans), but also less likely to acquire bad loans.

Table 6   Estimation Results: Cost Parameters

	Segment 1 (Hunter) Share: 68%	Segment 2 (Farmer) Share: 32%
Total Cost (θ_k^C)	1.970 (0.016)	3.322 (0.025)
Relative Acquisition Cost of Bad Loans $(\theta_k^{A_B})$	0.146 (0.014)	0.965 (0.065)
Relative Cost of Maintenance Effort (θ_k^M)	1.063 (0.008)	0.303 (0.037)
Relative Maintenance Cost of Bad Loans $(\theta_k^{M_B})$	0.964 (0.138)	2.968 (0.890)

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

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[16] We check the sensitivity of results in the online appendix using a different specification in which there four independent parameters for costs of acquisition and maintenance for good and bad loans. While the estimates remain qualitatively same, we retain the current specification which makes it easier to interpret the results (e.g., comparative advantage of each segment between two tasks).

6.2.1. Private Information and Structural Cost Parameter Estimates. Before we move on to counterfactuals, we briefly consider how not accounting for private information can bias the structural cost parameter estimates. Table 7 reports three sets of structural cost parameter estimates for the two salesperson segments. The first column (i) simply replicates the estimates from Table 6 for comparison. The second column (ii) reports the estimates with only non-learning periods, where private information is always present. The third column (iii), reports the estimates with all periods, but do not account for the fact that salespeople have no private information during learning periods. The estimates from columns (i) and (ii) are very similar, supporting our identification argument that the model can be identified entirely from non-learning periods, and learning periods merely provide overidentifying restrictions. Comparing columns (i) and (iii), we see that not accounting for the fact that salespeople do not have private information in the learning periods, significantly biases the structural estimates.

The signs of the bias from not accounting for the absence of private information is predictable. If the model assumes that salespeople can distinguish loan types during learning periods (i.e., right after transfer): (a) total cost (θ_k^C) is underestimated because salespeople with private information exert more effort in acquisition and maintenance overall because the effort is more effective with private information; (b) relative acquisition cost of bad loans $(\theta_k^{A_B})$ is underestimated as private information induces salespeople to acquire more bad loans; (c) relative cost of maintenance effort (θ_k^M) is overestimated for Hunters, who would focus on acquiring new loans with private information, but underestimated for Farmers, who would specialize in maintenance task; and (d) relative maintenance cost of bad loans $(\theta_k^{M_B})$ is overestimated because private information induces salespeople to selectively collect good loans.

7. Counterfactual Simulations

We examine the main research questions through three counterfactual policy simulations. The first counterfactual investigates how to combine performance metrics across multiple tasks in determining compensation. Specifically, we evaluate whether performance on acquisition and maintenance tasks should be combined multiplicatively or additively. The second counterfactual investigates the question of job design by comparing outcomes under a multitasking and specialization job design. Under multitasking, salespeople are

Table 7   Private Information and Structural Cost Parameter Estimates

	Segment 1 (Hunter)			Segment 2 (Farmer)		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Share	68%	67%	64%	32%	33%	36%
Total Cost (θ_k^C)	1.970	1.924	1.224	3.322	3.207	2.551
Relative Acquisition Cost of Bad Loans ($\theta_k^{A_B}$)	0.146	0.190	0.089	0.965	0.998	0.723
Relative Cost of Maintenance Effort (θ_k^M)	1.063	1.151	1.451	0.303	0.375	0.074
Relative Maintenance Cost of Bad Loans ($\theta_k^{M_B}$)	0.964	0.977	1.677	2.968	2.814	4.469

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

(i): Table 6, (ii): Non-learning periods only, (iii): Learning periods treated as having private information

responsible for both loan acquisition and maintenance tasks, while under specialization, each salesperson is responsible for either loan acquisition or maintenance. To highlight the trade-off between efficiency and incentive alignment, in the first two counterfactuals, we consider the case where the salesperson has private information. The last counterfactual investigates the effect of transfers on performance through its impact on salesperson private information.

For each counterfactual outcome, we simulate the salesperson's actions 500 times for each segment ("hunter" or "farmer"), fixing the salesperson's characteristics at their mean. Also, we do not rely on the first-order conditions in solving for optimal salesperson effort, but use a numerical approach that does not require derivatives (Nelder-Mead) because the maintenance index function is not differentiable everywhere. We consider multiple starting-points to ensure that the optimization algorithm converges to the global maximum.

7.1.   Multidimensional Incentive Plan Design

We first explore how to aggregate performance metrics across multiple tasks for the bonus. In particular, we compare the multiplicative aggregation approach used by the firm, i.e., Bonus $= A \times M$ against the more widely used additive aggregation. While there are more general compensation schemes than what we consider, our main purpose here is examining nuanced effects of multiplicative incentive scheme rather than deriving the optimal contract.[17] We consider the following additive aggregation Bonus $= wA + (2-w)M$ and find the optimal w to maximize the firm's profits, i.e., NPV of loans net incentive payout.

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[17] We consider an alternative scheme where hunters and farmers specialize in the acquisition and maintenance tasks respectively, and hunters' incentives are based on $A \times M$. The details are presented in the appendix. Overall, we leave the full characterization of the optimal incentive scheme design for future research.

Figure 7   Loan Performance: Multiplicative versus Additive

(a) Repayment Probability (%)

(b) Profit (1000 Pesos)
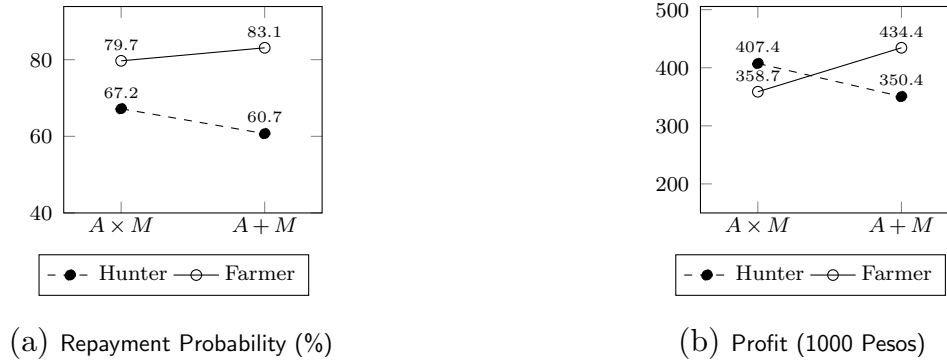
Using a grid search over $w \in \{0.25, 0.5, ..., 1.75\}$, we find $w = 0.5$ is optimal. In Table 8, we report the result for $Bonus = 0.5A + 1.5M$.

Table 8   Profit: Multiplicative versus Additive

Incentive Design	Multiplicative ($Bonus = A \times M$)			Additive ($Bonus = 0.5A + 1.5M$)		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	93.1	98.3	94.8	93.8	109.1	98.7
Acquisition - Bad	196.8	102.9	166.8	208.6	115	178.6
Maintenance - Good	79.5	81.6	80.2	79.6	92.8	83.8
Maintenance - Bad	115.4	78.8	103.7	104	93.4	100.6
Net Present Value (NPV)	470.6	424.7	455.9	414	502.5	442.3
Incentive Payout	63.8	66.0	63.8	63.6	68.0	65.0
Profit (NPV - Payout)	406.8	358.7	392.1	350.4	434.4	377.3

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

First, we find that under additive aggregation, the hunter segment acquires 6% more bad loans, and repayment is 6% lower. Thus, hunters expend more effort on the loan acquisition task on which they have a comparative advantage relative to loan collection. This leads to the total NPV of the hunters' loans going down by 12% and the profitability minus the incentive payout going down by 13.8%. In Figure 7, we visually present the key results in terms of the repayment probability and profit of the loans acquired and collected by each segment of salespeople. For hunters, the repayment probability and the total profit are higher under the multiplicative aggregation. This is consistent with the insight from MacDonald and Marx (2001) that the payoff complementarity induced by multiplicative aggregation can mitigate adverse specialization. The results are, however, reversed for

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

Given the natural intertemporal production and payoff complementarity—acquiring bad loans will hurt salesperson (and firm) future payoff, there is alignment in payoffs for firms and salespeople even under additive aggregation. By sharpening the contemporaneous payoff complementarity across tasks through multiplicative aggregation, the farmers end up shifting more of their effort to the acquisition tasks at which they are inefficient, overall reducing their productivity and profitability to the firm. However, despite the negative effect on farmers, the overall effect of multiplicative aggregation is to improve firm profits, because hunters account for a greater proportion of the salesforce at the firm.

7.2. Job Design and Task Allocation

In our second counterfactual analysis, we examine a largely unexplored question in the salesforce literature related to job design: how to allocate different tasks across salespeople whose capabilities are heterogeneous? For the purposes of this counterfactual, we consider two polar cases of specialization and multitasking. A natural assignment of tasks under the specialization design is to assign the acquisition task to "hunters," who are more effective at acquisition, and the maintenance task to "farmers," who are more effective at maintenance. By contrast, both segments are responsible for both acquisition and maintenance tasks under the multitasking case.

For multitasking, we use the same compensation plan used by the firm. For specialization, we solve the bank's optimization problem to obtain the optimal linear incentive as follows:[18]

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

$$\text{s.t. } N_t = N_t^G + N_t^B, \ R_t = R_t^G + R_t^B,$$

$$N_t^\omega = e_t^{A_\omega^*} + f(X_t; \beta_\omega) + \epsilon_t^{A_\omega}, \ R_t^\omega = e_t^{M_\omega^*} + h(X_t; \beta_\omega) + \epsilon_t^{M_\omega} \ (\omega \in \{G, B\}),$$

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

---

[18] We restrict the incentive plan to be a linear function of acquisition and maintenance performance and search for the optimal parameters of the incentive plan using grid search. In the online appendix, we report the profits under different values of k^A and k^M.

where Π_t is the profits for the bank, $C^H(\cdot)$ is the estimated effort cost function for the hunter segment and $C^F(\cdot)$ is the one for the farmer segment. Note that $e^A = \{e_t^A\}_{t=1}^{\infty}$, $e^M = \{e_t^M\}_{t=1}^{\infty}$, where $e_t^A = \{e_t^{A_G}, e_t^{A_B}\}$ and $e_t^M = \{e_t^{M_G}, e_t^{M_B}\}$. Solving the optimization problem, we find that the optimal linear compensation are $k^{A*} = 0.5$ and $k^{M*} = 0.75$.

Table 9 reports the acquisition and maintenance performance on each type of loan and overall firm profits (Net Present Value - incentive payout to salespeople) under the multitasking and specialization design, respectively. Figure 8 reports three measures of loan performance under the two types of job design. Table 9 shows that hunters acquire more loans, but particularly more bad loans under the specialization scheme than under the multitasking. Similarly, farmers maintain more good loans under the specialization and only slightly fewer bad loans. These findings confirm the overall efficiency gain of the specialization design.

However, these efficiency gains are more than overwhelmed by moral hazard. Figure 8a shows that hunters acquire significantly more bad loans under the specialization and the repayment probability is significantly lower as farmers are not good at collecting the bad loans (see Figure 8b). Overall, this leads to a 35% lower profit under specialization (see Figure 8c).

We elaborate further on how specialization hurts the firm, despite the efficiency gain in both segments. First, since hunters do not internalize the future consequences of acquiring bad loans, they exploit private information much more under specialization and acquire more bad loans than they do under the multitasking. Second, since farmers are good at collecting good loans, but not good at collecting bad loans, most of the bad loans acquired by hunters end up being delinquent. Together, profitability is significantly lower under the specialization scheme.

While in this analysis, we have focused on the polar cases of specialization and multitasking to generate insights into the trade-off between efficiency and incentive alignment, we note that other variations in task allocation and compensation plans are feasible. For example, one could create a team structure, where performance is measured at the team level, but team members have specialized tasks. Although we consider a few alternative job allocation/incentive schemes in the appendix, we leave the full problem of optimal job design along all of these dimensions for future research.

Table 9   Profitability: Multitasking versus Specialization

Job Design	Multitasking			Specialization		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	93.1	98.3	94.8	135.1		135.1
Acquisition - Bad	196.8	102.9	166.8	300.9		300.9
Maintenance - Good	79.5	81.6	80.2		95.9	95.9
Maintenance - Bad	115.4	78.8	103.7		111.3	111.3
Net Present Value (NPV)	470.6	424.7	455.9			372.7
Incentive Payout	63.8	66.0	63.8			80.4
Profit (NPV - Payout)	406.8	358.7	392.1			292.3

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

Figure 8   Loan Performance: Multitasking versus Specialization
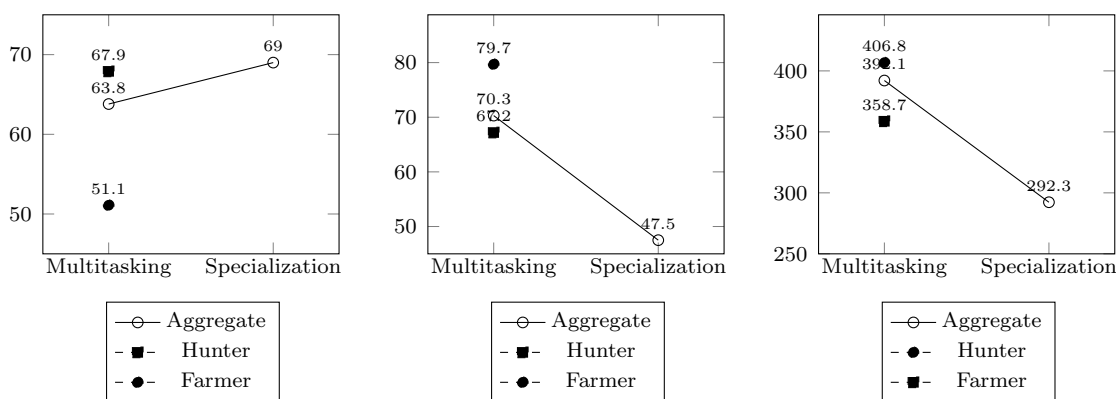
(a) Share of Bad Loans (%)   (b) Repayment Probability (%)   (c) Profit (1000 Pesos)

7.3.   Job Transfers and Private Information

Our final counterfactual examines the role of the transfer policy in eliminating private information and how the policy affects the firm's profits. This is an interesting counterfactual because our estimation results imply that private information can be a double-edged sword by helping salespeople acquire less risky loans and making better maintenance decisions while leading to salesperson moral hazard.

To quantify the effects of private information, we simulate salesperson behavior using the estimated policy function when salespeople have private information (i.e., when they are not transferred) and the estimated policy function when they do not have private information (i.e., when they are transferred with 100% probability). Table 10 and Figure

Figure 9 **Loan Performance: Without versus With Private Information**

(a) Share of Bad Loans (%) (b) Repayment Probability (%) (c) Profit (1000 Pesos)
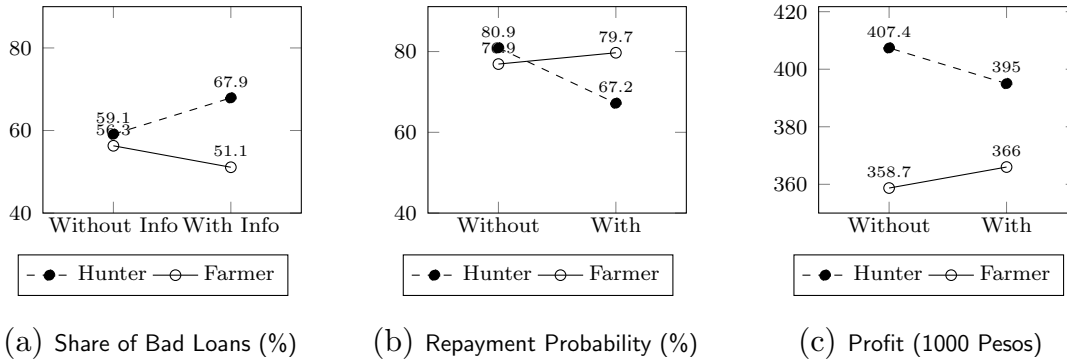
9 describe salesperson performance and profitability under two cases. With private information, we find hunters abuse their knowledge to acquire more bad loans by 8.8% (Figure 9a), which are repaid less by 13.7% (Figure 9b), and generate lower profit by 3% (Figure 9c). By contrast, farmers take advantage of private information to be involved in fewer new bad loans by 5.2% (Figure 9a), selectively monitor and better collect loans by 2.8% (Figure 9b), and generate higher profit by 2% (Figure 9c). Overall, our simulation results suggest that the firm can improve profits by transferring *hunters* more frequently than farmers, instead of the current random policy, where all salespeople are equally likely to be transferred.

Table 10 **Profitability: Without versus With Private Information**

	Without Private Information			With Private Information		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	93.1	98.3	94.8	85.4	94.8	88.4
Acquisition - Bad	196.8	102.9	166.8	123.5	122.3	123.1
Maintenance - Good	79.5	81.6	80.2	79.3	79.2	79.3
Maintenance - Bad	115.4	78.8	103.7	89.7	87.8	89.1
Net Present Value (NPV)	470.6	424.7	455.9	450.5	434.5	445.4
Incentive Payout	63.2	65.9	63.8	55.5	68.5	59.7
Profit (NPV - Payout)	407.4	358.7	392.1	395.0	366.0	385.7

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

8. Conclusion

In this paper, we broaden the focus of empirical research in salesforce management, which was primarily focused on single task settings with unidimensional incentives to multitasking

settings with multidimensional incentives, where salespeople also have private information about customers. This allowed us to expand the substantive focus in salesforce management to questions of performance aggregation across tasks, job design, and management of private information.

To this end, we developed a new dynamic structural model of multitasking with multidimensional incentives, where there is an intertemporal tradeoff in effort allocated across tasks. The model also allows for employee moral hazard by allowing employees to have private information about customers, which affects their marginal cost of reaching performance goals that are misaligned with the firm's objectives. Our identification and estimation strategies address various challenges involved in such a multitasking model with private information. We apply our model and estimation methods in a rich empirical microfinance setting. Finally, using the estimates of our structural model, we conduct counterfactual analysis on managerially relevant questions on multidimensional incentive design, job design, and task allocation for salespeople in the presence of complementarities between tasks, and job transfers that impact private information.

Given the widespread prevalence of multitasking, multidimensional incentives, and employee private information, our structural model can potentially serve as a workhorse model in many settings across the fields of marketing, operations management, organizational behavior, and organizational economics. Special cases (or minor adaptations) of the model can be used in settings without dynamics when tasks have no intertemporal linkages and those without private information. The model can be even applied to single task settings with multidimensional incentives. For example, consider a customer support person, with incentives based on composite performance metrics such as customer satisfaction and average time per call. Even though there is only a single task of providing service, the person needs to balance effort on the satisfaction and service time dimensions to maximize incentives.

While the paper expanded the range of issues that can be addressed through structural modeling in salesforce management, there remain issues that we abstracted away or did not account for due to a lack of relevance for our empirical application. These are potentially fertile areas of study for future research. First, while we considered the extreme cases of specialization and multitasking, we abstracted away from other potential job designs, including team-based incentives where different members are responsible for different tasks.

There could also be settings where incentive alignment might be created through markets for acquired assets. Second, we treated issues of optimizing each component of the compensation plan, such as how to set acquisition quotas or the functional form linking maintenance performance to incentives as beyond the scope of this paper. Third, while our application is for loan officers in the banking sector and there are parallels with customer acquisition and retention tasks in customer relationship management settings, it would be useful to consider an explicit application in a CRM setting. In such settings, customer maintenance tasks can have multiple components involving customer growth and retention. Finally, Holmström and Milgrom (1991) discuss the accuracy and measurability of performance metrics as critical in job and incentive design. It would be useful to consider multiple tasks where the accuracy of measurement might differ across tasks (e.g., sales is more precisely measured than customer satisfaction) and how these differences impact job and incentive design.

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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 how the maintenance index depends 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.   Learning Period for Salesperson Private Information

To assess whether the absence of private information impacts effort allocation, we test whether the IRR of loans acquired and the probability of loan delinquency differ (conditional on credit rating) during the learning period relative to other periods. To empirically assess the appropriate length of the learning period, we use different lengths of learning periods (1,2... months) in the regressions.

   Table A2 presents the regression results. The DV in the first two columns is the acquired loans' IRR; for the last two columns, it is the delinquency probability of loans. The independent variable (Private Information) denotes a dummy variable for the learning period (1 or 2 months as noted in each column). Since IRR and delinquency are impacted by credit ratings, we include both the main effect of credit rating and interaction terms with private information.

   From Column (1), we find that for the one month learning period, officers with private information acquire significantly lower quality loans than those without, except for credit rating 2 loans, while from Column (2), the negative effect disappears for the two month learning period. This finding suggests that it takes about a month for salespeople to learn loan types for acquisition. Similarly, from Column (3), we find that the delinquency probability of loans is higher for credit ratings 3, 4 and 5, (these account for most loans) for the one-month learning period, while the effects are insignificant for the two-month learning period. This again suggests that it is reasonable to assume that the length of the learning period for loan maintenance is about one month.

C.   Estimation of Production Function

C.1.   Backfitting Algorithm

To estimate the semi-parametric salesperson production function, we apply the backfitting algorithm (Buja et al. 1989 and Bickel et al. 2005):

Table A2   Assumption on Salesperson Learning Period of Private Information

	(1) Acquisition IRR	(2) Acquisition IRR	(3) Maintenance Pr(Delinquent)	(4) Maintenance PR(Delinquent)
DV				
Learning period	1 month	2 months	1 month	2 months
Private Info	-3.812***	-1.417	0.00297	-0.0107
	(1.112)	(1.064)	(0.0123)	(0.0118)
Private Info * Rating 2	3.988**	5.145***	0.0392*	0.0147
	(1.834)	(1.730)	(0.0202)	(0.0192)
Private Info * Rating 3	-2.034	-0.178	-0.0329**	-0.0133
	(1.472)	(1.422)	(0.0162)	(0.0158)
Private Info * Rating 4	-1.806	-0.0819	-0.0668***	-0.0116
	(1.225)	(1.178)	(0.0135)	(0.0131)
Private Info * Rating 5	-2.525**	0.637	-0.0887***	-0.00555
	(1.140)	(1.095)	(0.0126)	(0.0122)
Rating 2	6.864***	8.059***	-0.0844***	-0.0706***
	(0.685)	(0.727)	(0.0188)	(0.0175)
Rating 3	21.43***	23.72***	-0.189***	-0.223***
	(0.550)	(0.587)	(0.0151)	(0.0144)
Rating 4	33.63***	36.55***	-0.387***	-0.466***
	(0.468)	(0.502)	(0.0125)	(0.0119)
Rating 5	42.00***	45.31***	-0.486***	-0.600***
	(0.441)	(0.475)	(0.0116)	(0.0110)
Intercept	46.11***	43.54***	0.717***	0.748***
	(0.432)	(0.465)	(0.0113)	(0.0106)
N	100,250	90,986	100,250	90,986
R-sq	0.154	0.175	0.238	0.265

1. Initialize $\hat{\beta}^{A_G}$, $\hat{\beta}^{A_B}$, $\hat{\beta}^{M_G}$, $\hat{\beta}^{M_B}$ and $\hat{\Sigma}$.

2. Estimate $\hat{\lambda}^{A_G}$, $\hat{\lambda}^{A_B}$, $\hat{\lambda}^{M_G}$ and $\hat{\lambda}^{M_B}$ from the following moment condition:

$$
E\left(\begin{bmatrix} N_{jt}^G - f(X_{jt}^{A_G}; \hat{\beta}^{A_G}) \\ N_{jt}^B - f(X_{jt}^{A_B}; \hat{\beta}^{A_B}) \\ R_{jt}^G - f(X_{jt}^{M_G}; \hat{\beta}^{M_G}) \\ R_{jt}^B - f(X_{jt}^{M_B}; \hat{\beta}^{M_B}) \end{bmatrix} \Big| S_{jt}\right) = \begin{bmatrix} \hat{e}_{jt}^{A_G}(S_{jt}; \lambda^{A_G}) \\ \hat{e}_{jt}^{A_B}(S_{jt}; \lambda^{A_B}) \\ \hat{e}_{jt}^{M_G}(S_{jt}; \lambda^{M_G}) \\ \hat{e}_{jt}^{M_B}(S_{jt}; \lambda^{M_B}) \end{bmatrix}.
\tag{9}
$$

3. Predict $\hat{e}_{jt}^{A_G}(S_{jt}; \hat{\lambda}^{A_G})$, $\hat{e}_{jt}^{A_B}(S_{jt}; \hat{\lambda}^{A_B})$, $\hat{e}_{jt}^{M_G}(S_{jt}; \hat{\lambda}^{M_G})$ and $\hat{e}_{jt}^{M_B}(S_{jt}; \hat{\lambda}^{M_B})$, based on the estimates of $\hat{\lambda}^{A_G}$, $\hat{\lambda}^{A_B}$, $\hat{\lambda}^{M_G}$ and $\hat{\lambda}^{M_B}$.

4. Estimate $(\hat{\beta}^{A_G}, \hat{\beta}^{A_B}, \hat{\beta}^{M_G}, \hat{\beta}^{M_B}, \hat{\Sigma})$ in $f(\cdot)$ functions by MLE constructed by $\epsilon_{jt} = (\epsilon_{jt}^{A_G}, \epsilon_{jt}^{A_B}, \epsilon_{jt}^{M_G}, \epsilon_{jt}^{M_B})$, which follow a Multinomial Normal distribution.

$$
(\hat{\beta}^{A_G}, \hat{\beta}^{A_B}, \hat{\beta}^{M_G}, \hat{\beta}^{M_B}, \hat{\Sigma}) = \arg\max L\left(\begin{bmatrix} N_{jt}^G - \hat{f}(X_{jt}^{A_G}) - \hat{e}_{jt}^{A_G}(S_{jt}) \\ N_{jt}^B - \hat{f}(X_{jt}^{A_B}) - \hat{e}_{jt}^{A_B}(S_{jt}) \\ R_{jt}^G - \hat{f}(X_{jt}^{M_G}) - \hat{e}_{jt}^{M_G}(S_{jt}) \\ R_{jt}^B - \hat{f}(X_{jt}^{M_B}) - \hat{e}_{jt}^{M_B}(S_{jt}) \end{bmatrix}\right),
$$

where $L(\cdot)$ is the log-likelihood function of ϵ_{jt}, i.e., $\sum_j \sum_t \log \phi(\epsilon_{jt})$ with the density function of the Multinomial Normal distribution.

5. Iterate $2 - 4$ until convergence.

In Step 2, we make use of a machine learning approach to allow for flexible effort policy functions, where $N_{jt}^G - \hat{f}(X_{jt}^{A_G})$ is the outcome for prediction and S_{jt} is the explanatory variables. Note that the left-hand

side variables are all scalar variables given β's. It is important not to make a restrictive assumption on the functional form, which might lead to biased structural parameter estimates. Specifically, we use the random forest algorithm due to its high predictive power and flexibility for the nonparametric estimation. Moreover, we combine the algorithm with cross-sample fitting to eliminate overfitting and ensure the consistency of the estimator under a high-dimensional effort function (Chernozhukov et al. 2018a), motivated by Newey and Powell (2003). To do so, we randomly divide the observations into the main and auxiliary samples, each of which takes up 50% of the data; we obtain the estimates only from the main sample only and those from the auxiliary sample only, and we then average the results across the samples.

C.2. Incorporating unobserved heterogeneity

We incorporate the unobserved latent segments of salespeople by the method developed by Arcidiacono and Jones (2003). Following the application in Chung et al. (2013) that use the same method for the uni-dimensional effort policy function, we compute the log-likelihood of simultaneously observing salesperson j's acquisition and maintenance outcomes $(N_{jt}^G, N_{jt}^B, R_{jt}^G, R_{jt}^B)$ given segment-level parameters and the persistent segment k to which salesperson j belongs:

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

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

$$\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} q_{jk} L_{jkt}, \tag{10}$$

where

$$q_{jk} = Pr(k | N_{jt}^G, N_{jt}^B, R_{jt}^G, R_{jt}^B; e, \beta, \Sigma, p) = \frac{p_k \left(\prod_{t=1}^{T} L_{jkt} \right)}{\sum_{k=1}^{K} p_k \left(\prod_{t=1}^{T} L_{jkt} \right)} \tag{11}$$

and p_k is the fraction of segment k.

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

1. Compute $q_{jk}^{(m+1)}$ using equation (11) with $e^{(m)}, \beta^{(m)}, \Sigma^{(m)}$ and $p^{(m)}$.

2. Obtain $e^{(m+1)}, \beta^{(m+1)}$ and $\Sigma^{(m+1)}$ by maximizing the full information maximum likelihood, weighted by $q_{jk}^{(m+1)}$ in equation (10).

3. Update $p^{(m+1)}$ by taking the average of $q_{jk}^{(m+1)}$.

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

D. Additional Counterfactual Simulations

D.1. Specialization Job Design, but Incentives Linked to Acquisition and Repayment Outcomes

In this section, we consider an alternative incentive design under the specialization job allocation. In the main text, each salesperson is assigned to only one task, and her bonus is based on the performance of the

assigned task. An alternative incentive under the specialization scheme is an incentive contract where the hunter is evaluated based on *both* acquisition and maintenance performances. This incentive scheme could help solve the incentive misalignment issue of the specialization job design that we consider in the main text, where the issue is that the hunter does not care about the future profitability of newly-acquired loans.

We simulate specialized salespeople's behaviors under the compensation plan that rewards hunters' efforts to acquire good loans in Table A3. Following Table 9, we choose the incentive plan to be $Bonus = 0.5A$ for hunters and $Bonus = 0.75M$ for farmers, when specialized hunters are rewarded in terms of acquisition performance only. When hunters are incentivized based on both acquisition and maintenance performances, their incentive plan is chosen to be $Bonus = A \times M$, whereas farmers' incentive plan remains as $Bonus = 0.75M$. Farmers are not evaluated in terms of hunters' acquisition performances in any case because acquisition outcomes are realized before their maintenance effort and beyond farmers' control at all.

Table A3 shows the acquisition and maintenance performance of good and bad loans; Net Present Value (NPV) of loans and incentive payout; and the firm's profit under two incentive designs for specialized salespeople. We find that the profit increases by 33% if hunters' incentive depends not only on acquisition performance but also on maintenance performance. This happens because hunters now care about the quality of acquired loans and hence do not acquire too many bad loans.

Table A3   **Profitability: Hunters incentivized on Acquisition only versus Hunters incentivized on Acquisition and Maintenance**

Hunters' Incentive Design	$Bonus = 0.5A$			$Bonus = A * M$		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	135.1		135.1	120.5		120.5
Acquisition - Bad	300.9		300.9	236.2		236.2
Maintenance - Good		95.9	95.9		113.7	113.7
Maintenance - Bad		111.3	111.3		96.8	96.8
Net Present Value (NPV)			372.7			464.7
Incentive Payout			80.4			76.9
Profit (NPV - Payout)			292.3			387.8

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

Although this incentive scheme seems more profitable, our interview with the firm tells us that it is not feasible to implement it. The firm's main concern lies in the perceived unfairness across salespeople because hunters would not accept that their bonus partly depends on farmers' performances. For example, a loan default is attributed not only to *ex ante* low quality of loans, which a hunter is responsible for, but also a lack of maintenance effort by a farmer. Thus, a hunter cannot be penalized by loan defaults when he's only in charge of loan acquisition. Furthermore, the random transfer policy is another obstacle to justify the incentive scheme. Right after transfers, farmers are not capable of collecting loans well. It is hard to convince hunters that their compensation partly depends on whether their new loans are maintained by

transferred farmers or not. Despite the difficulty of implementing the incentive scheme in practice, we believe the simulation sheds light on the way to address the incentive misalignment problem.

D.2.   Multitasking Job Design with Loan Repayment Only based Incentive

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

To do so, we simulate a salesperson's behavior under the compensation plan based on the amount of loan repayment. The incentive plan is chosen to be $Bonus = RepayAmt/(4*Quota)$, which normalizes total repayment amount by the acquisition quota for the average duration of loans (4 months) to compensate salespeople based on *repayment amount of loans per targeted acquisition amount*. Like other counterfactual simulations in Section 7, a salesperson is assumed to have private information about customers in every period and is not affected by the transfer policy.

Table A4 compares the acquisition and maintenance performance of good and bad loans; Net Present Value (NPV) of loans and incentive payout; and the firm's profit from two segments of salespeople under the two incentive plans. The profit considering Net Present Value of loans and incentive payout increases by 4% if the compensation scheme is changed to the repayment amount-based plan. Figure A1 visually represents the change in share of bad loans; repayment probability; and profit of each segment, which shows that if the two tasks are not separated in terms of performance metrics, a salesperson in the hunter segment is less likely to acquire bad loans by 8% (see Figure A1a), because of no incentive on the volume of acquisition, collect more loans by 13% (see Figure A1b) because of fewer bad loans and more effort in loan collection; and generate higher profits in the end (see Figure A1c). There is little difference in farmers' performance between plans, which shows that farmers' incentive is already aligned well with the firm's incentive under the current compensation plan.

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

Table A4   **Profitability: Current versus Repayment Amount-based Metrics**

Incentive Design	Current metrics $(Bonus = A \times M)$			Repayment amount-based metric $(Bonus = RepayAmt/(4*Quota))$		
	Hunter	Farmer	Aggregate	Hunter	Farmer	Aggregate
Acquisition - Good	93.1	98.3	94.8	93.8	94.3	94.0
Acquisition - Bad	196.8	102.9	166.8	139.9	93.6	125.1
Maintenance - Good	79.5	81.6	80.2	80.2	81.0	80.5
Maintenance - Bad	115.4	78.8	103.7	107.3	75.8	97.2
Net Present Value (NPV)	470.6	424.7	455.9	497.9	423.9	474.2
Incentive Payout	63.8	66.0	63.8	62.5	65.4	63.4
Profit (NPV - Payout)	406.8	358.7	392.1	435.5	358.5	410.8

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

Figure A1   **Loan Performance: Current versus Repayment Amount-based Metrics**
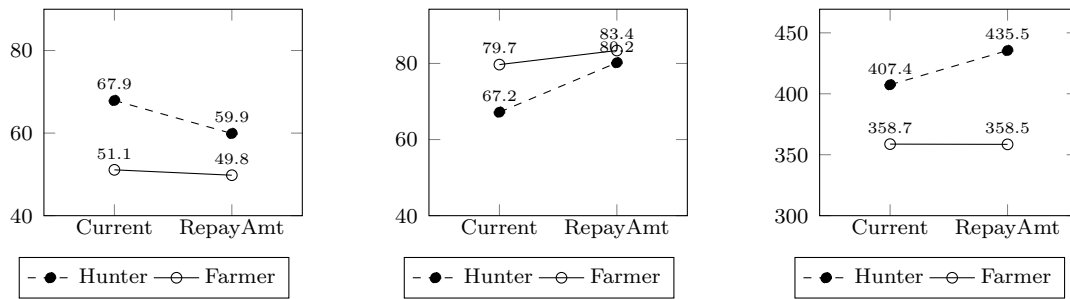
(a) Share of Bad Loans (%)   (b) Repayment Probability (%)   (c) Profit (1000 Pesos)

Online Appendix

OA.1.   Variable Description for Loan Type Classification

Table OA1 lists the variables we put in the random forest model to estimate equation (OA1).

Table OA1   **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)

OA.2.   Forward-simulation Procedure

In this section, we explain the forward-simulation process in Step 2 of the estimation procedure, which follows Bajari et al. (2007). The algorithm that calculates 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 $e_{kt}(S_{jt}; \hat{\lambda}_k)$ and the impact of exogenous shifters using estimated $\hat{\beta}_k$ at the first stage as $f(X_{jt}; \hat{\beta}_k)$ for each type of outcomes.

4. Unanticipated shocks for each performance ϵ_{jt} are drawn from a multivariate normal distribution of mean zero and estimated covariance $\hat{\Sigma}_k$.

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

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

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

OA.3. Other Estimation Results

OA.3.1. Random Forest Results in Step 1a Figure OA1 shows the importance of each variable in classifying the loans. Variable importance represents the normalized percentage of variance explained by each variable, a measure of how well out-of-bag predictions explain the target variance of the training set.[19] We find that the interest rate, the time of acquisition, and the duration of the loan are the top three variables to predict ex-post IRR.

OA.3.2. Quota Setting This section reports the estimation results of the quota setting. Although we know that the acquisition quota for a continuing salesperson increase in response to the volume of her existing loans, the company does not reveal the exact function to set quota. Hence, we approximate it with the following transition function.

$$Q_{j,t+1} = \sum_{l=0}^{3} \kappa_l \Lambda_l(O_{j,t+1}) \Lambda_l(Q_{jt}) + \mu_{t+1} + \varepsilon_{j,t+1}, \tag{12}$$

where $\Lambda_l(.)$ represents the lth basis of the 3rd 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 $t+1$. Table OA2 reports the estimation results for

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[19] Similar to pseudo R-squared measure, the percentage of variance explained is computed as $1 - MSE/VarY$, where MSE is mean squared error of out-of-bag predictions for each variable compared to the the outcome variable, and $VarY$ is variance of the outcome variable.

Figure OA1   Variable Importance
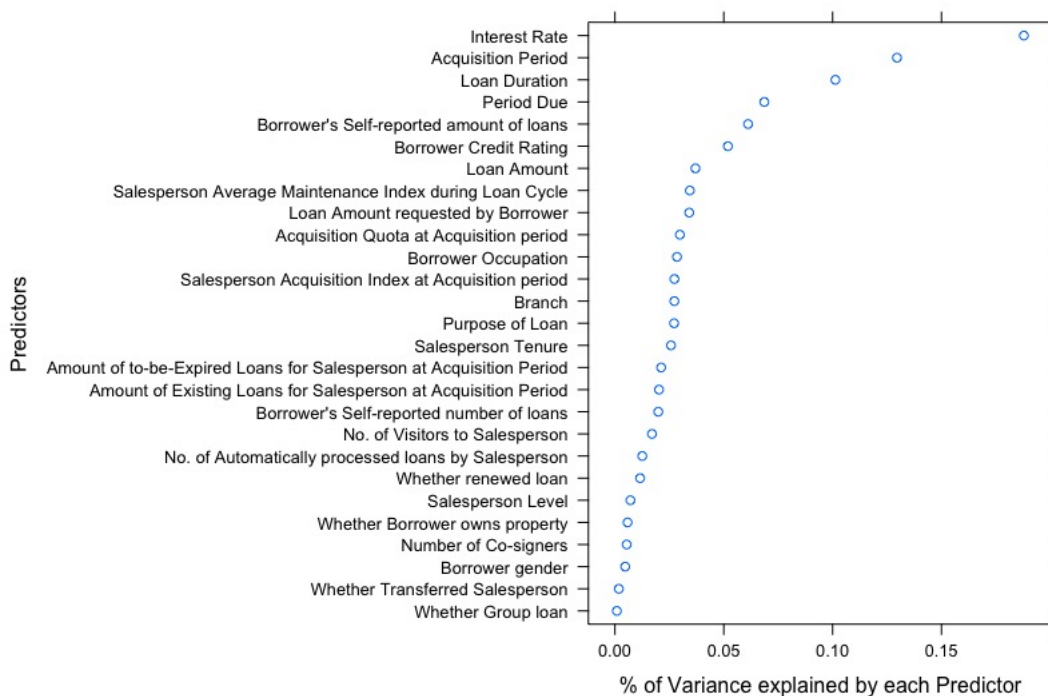
continuing salespeople in the first two columns and those for transferred salespeople in the third and fourth columns. The first two columns show that there is a positive relationship between the current quota and the next period quota for the continuing salespeople, while the last two columns show that there is no such a relationship for transferred salespeople as expected.

The positive relationship between $Q_{j,t}$ and $Q_{j,t+1}$ implies that there might be ratcheting incentive for salespeople. Although it does not affect our counterfactual analyses, it is interesting to quantify the effect of salespeople ratcheting. In our context, the ratcheting incentive is not necessarily harmful for the company, because salespeople engage less in adverse customer selection with ratcheting. It is an interesting future research question to ask.

OA.3.3.   Covariance Matrix of Shocks   Table OA3 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 $\epsilon_k^{M_B}$).

OA.4.   Robustness Checks

OA.4.1.   Salesperson Compensation States in Loan Classification   Classifying loans into good and bad loans in the main text, we use the average state of salesperson j only, to control each salesperson's

Table OA2   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

Table OA3   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

time-varying effort in collecting the loan. We check the robustness of our result by using the average states across *all* salespeople instead of each salesperson's compensation state as an input to infer loan quality. Table OA4 shows the structural parameter estimates under the new loan classification. Although the exact estimates changed, the qualitative result remains same that (i) we find two distinct segments of salespeople, one of which has comparative advantage on new customer acquisition (Hunter) and the other on customer maintenance (Farmer); (ii) Hunter segment finds bad loans much less costly to acquire than good loans, so are likely to chase for easier-to-acquire, but lower quality loans under specialization or additive incentive scheme; and (iii) Salespeople in the Farmer segment find bad loans harder to maintain, thus they would suffer if specialized Hunters bring in bad loans only under specialization.

OA.4.2.   Specification of Loan Officer Production Function   We also check the robustness of our results under the specification of production function that includes (i) main effect of tenure and (ii) month

Table OA4   Robustness Check 1: Average Salesperson Compensation States Included in Loan Classification Structural Cost Parameter Estimates

	Segment 1 (Hunter) Share: 66%	Segment 2 (Farmer) Share: 34%
Total Cost (θ_k^C)	1.234 (0.012)	2.953 (0.049)
Relative Acquisition Cost of Bad Loans $(\theta_k^{A_B})$	0.090 (0.028)	0.116 (0.019)
Relative Cost of Maintenance Effort (θ_k^M)	1.361 (0.057)	0.301 (0.081)
Relative Maintenance Cost of Bad Loans $(\theta_k^{M_B})$	1.700 (0.074)	3.797 (0.208)

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

fixed effects in control variables X_{jt}. W find that the seasonality does not play a role in this setting, and the structural parameters are estimated to be qualitatively similar as in Tables OA5 and OA6.

OA.4.3. Specification of Cost Function   Instead of the specification of cost function in the main text, $C(e_{jt};\Theta_j) = \theta_j^C \left[(e_{jt}^{A_G} + \theta_j^{A_B} e_{jt}^{A_B}) + \theta_j^M (e_{jt}^{M_G} + \theta_j^{M_B} e_{jt}^{M_B}) \right]^2$, we check the sensitivity of our result under the specification where each effort has an independent cost parameter: $C(e_{jt};\Theta_j) = \left[\theta_j^{A_G} e_{jt}^{A_G} + \theta_j^{A_B} e_{jt}^{A_B} + \theta_j^{M_G} e_{jt}^{M_G} + \theta_j^{M_B} e_{jt}^{M_B} \right]^2$.

Note that these two specifications are observationally equivalent. Hence, it is possible to convert each parameter from the original specification to the one in the new specification. For example, $\theta_j^{A_G}$ in the new specification corresponds to $\sqrt{\theta_j^C}$ in the original specification. Table OA7 shows the estimated parameters from the independent specification and corresponding derived estimates from the original specification. The table shows that the estimates are close to each other.

OA.4.4. Standard Errors under Alternative Perturbations of Moment Inequalities   In the main text, we perturb the policy function for obtaining moment inequalities by adding a normal distribution with mean 0 and the standard deviation of 0.01. In this subsection, we check the sensitivity of our standard error estimates with respect to the degree of perturbation in Table OA8. As is well-known, the estimated standard errors tend to be bigger as we add larger perturbations. Unfortunately, there is not a well-grounded choice of the perturbation level. The parameters are still significant overall, although insignificant under larger perturbations (e.g., 0.5 or 1).

OA.5. Details on Specialized Salespeople's Incentive Plan and Multitasking Salespeople's Additive Aggregation Plan

The first counterfactual simulation to study multidimensional incentive plan design requires us to find the additive incentive plan, i.e., $Bonus = wA + (2-w)M$, that is comparable to the current multiplicative plan. In other words, we need to find profit-maximizing weight on Acquisition task relative to Maintenance task (w) for salespeople under the additive plan. As w goes up, salespeople, hunters in particular, are likely to focus their effort on acquisition of new loans and not to collect enough loans to make profit for the company. This is equivalent to forcing all salespeople to specialize in acquisition in the extreme case, e.g., $w=0$. A very high w, on the contrary, makes salespeople shirk prospecting for new customers. We do the grid search over w when $w \in \{0.25, 0.5, ..., 1.75\}$ in Figure OA2 to compare the profit (Net Present Value of loans - Incentive

Table OA5 **Robustness Check 2: Specification of Loan Officer Outcome Functions**

	Segment 1		Segment 2	
Segment Share	62%		38%	
	Coefficient	SE	Coefficient	SE
Acquisition of Good Loans				
Intercept	-6.92	0.060	-8.83	0.079
Average Quota (branch)	40.35	0.293	42.64	0.284
Tenure	0.00	0.015	0.00	0.021
Tenure * Avrg Quota (branch)	-8.76	0.073	-9.02	0.084
Feb 09	-8.46	0.034	-8.00	0.080
Mar 09	-10.67	0.094	-10.25	0.088
Apr 09	0.15	0.013	-0.01	0.030
May 09	0.06	0.024	0.00	0.025
Jun 09	-5.83	0.031	-4.04	0.040
Jul 09	-1.81	0.016	0.00	0.013
Aug 09	0.09	0.011	-0.01	0.033
Sep 09	0.00	0.051	0.00	0.003
Oct 09	-4.00	0.060	-3.66	0.033
Nov 09	0.00	0.008	0.00	0.015
Dec 09	-147.29	0.015	-0.05	2.132
Jan 10	-0.02	0.027	-0.02	0.025
Feb 10	-3.34	0.035	-3.01	0.039
Acquisition of Bad Loans				
Intercept	-15.30	0.080	-10.87	0.089
Average Quota (branch)	7.80	0.148	9.60	0.067
Tenure	0.00	0.007	0.01	0.003
Tenure * Avrg Quota (branch)	3.97	0.002	4.40	0.029
Feb 09	4.67	0.019	-0.01	0.062
Mar 09	10.40	0.064	5.91	0.074
Apr 09	6.04	0.044	0.00	0.120
May 09	-0.09	0.034	0.00	0.007
Jun 09	9.58	0.009	0.00	0.081
Jul 09	8.60	0.001	0.00	0.067
Aug 09	5.94	0.002	0.00	0.050
Sep 09	20.40	0.114	15.95	0.112
Oct 09	20.40	0.121	15.17	0.130
Nov 09	19.77	0.129	14.83	0.134
Dec 09	0.00	0.006	0.00	0.014
Jan 10	0.00	0.092	-4.25	0.042
Feb 10	-0.13	0.026	-5.26	0.051
Maintenance of Good Loans				
Intercept	-4.33	0.034	-3.62	0.019
Average Quota (branch)	0.00	0.019	2.83	0.033
Tenure	0.47	0.002	0.49	0.002
Tenure * Avrg Quota (branch)	-0.46	0.011	-0.73	0.005
Feb 09	0.00	0.010	-0.55	0.017
Mar 09	0.01	0.000	0.00	0.012
Apr 09	-0.01	0.101	0.04	0.032
May 09	2.66	0.009	0.00	0.015
Jun 09	0.00	0.019	-0.92	0.015
Jul 09	0.00	0.018	-1.10	0.010
Aug 09	3.12	0.004	1.68	0.014
Sep 09	2.91	0.006	1.51	0.016
Oct 09	2.57	0.009	1.23	0.013
Nov 09	2.20	0.020	0.85	0.013
Dec 09	38.99	0.612	3.08	2.612
Jan 10	2.81	0.007	1.36	0.019
Feb 10	2.50	0.002	0.00	0.015
Maintenance of Bad Loans				
Intercept	-0.17	0.000	0.01	0.107
Average Quota (branch)	0.02	0.143	-6.83	0.077
Tenure	0.87	0.004	0.00	0.014
Tenure * Avrg Quota (branch)	-1.55	0.012	1.85	0.032
Feb 09	12.83	0.095	15.32	0.138
Mar 09	-35.29	0.192	-33.20	0.231
Apr 09	23.77	0.020	0.00	0.463
May 09	0.00	0.020	-2.62	0.000
Jun 09	-26.38	0.001	-24.32	0.208
Jul 09	-20.34	0.123	-18.44	0.166
Aug 09	-12.18	0.086	-10.84	0.134
Sep 09	-14.28	0.160	-12.56	0.151
Oct 09	-14.93	0.154	-13.45	0.141
Nov 09	-15.27	0.139	-13.76	0.136
Dec 09	0.14	0.008	0.00	0.018
Jan 10	-14.99	0.140	-13.59	0.128
Feb 10	-15.79	0.165	-14.83	0.147

Table OA6   Robustness Check 2: Specification of Loan Officer Outcome Functions

Structural Cost Parameter Estimates

	Segment 1 (Hunter) Share: 62%	Segment 2 (Farmer) Share: 38%
Total Cost (θ_k^C)	1.2243	2.8774
Relative Acquisition Cost of Bad Loans ($\theta_k^{A_B}$)	0.0898	0.7321
Relative Cost of Maintenance Effort (θ_k^M)	1.4512	0.2854
Relative Maintenance Cost of Bad Loans ($\theta_k^{M_B}$)	1.6772	4.7245

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

Table OA7   Robustness Check 3: Independent Parameters Model Estimates and

Corresponding Derived Estimates from Original Specification

	Segment 1 (Hunter) Share: 68%		Segment 2 (Farmer) Share: 32%	
	Estimate	Corresponding Derived Estimate	Estimate	Corresponding Derived Estimate
Acquisition Cost of Good Loans ($\theta_k^{A_G}$)	1.2831	1.4036	1.7317	1.8226
Acquisition Cost of Bad Loans ($\theta_k^{A_B}$)	0.2403	0.2049	1.3573	1.7588
Maintenance Cost of Good Loans ($\theta_k^{M_G}$)	1.2000	1.4920	0.4560	0.5523
Maintenance Cost of Bad Loans ($\theta_k^{M_B}$)	1.4595	1.4383	1.6247	1.6391

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

**Table OA8   Robustness Check 4: Standard Errors**

	θ_1^C	$\theta_1^{A_B}$	θ_1^M	$\theta_1^{M_B}$	θ_2^C	$\theta_2^{A_B}$	θ_2^M	$\theta_2^{M_B}$
	Segment 1				Segment 2			
Coefficient	1.970	0.146	1.063	0.964	3.322	0.965	0.303	2.968
Perturbation	Standard Errors							
0.001	0.001	0.002	0.001	0.014	0.001	0.001	0.001	0.050
0.01	0.016	0.014	0.008	0.138	0.025	0.065	0.037	0.089
0.1	0.066	0.035	0.025	0.160	0.094	0.086	0.042	0.042
0.5	0.617	0.101	0.125	0.148	0.510	1.171	0.235	0.137
1	0.570	0.148	0.244	0.092	0.660	0.680	0.257	0.226

Payout to salespeople) under different weights on A relative to M. The exercise finds that $w = 0.5$, which assigns higher weight on the maintenance task, generates the highest profit from the salespeople. A smaller w slightly hurts the firm's profit because farmers do not exert enough effort to acquire new loans. Any bigger w than 0.5 motivates hunters to acquire unnecessarily many bad loans which are not collected in the end. We report the detailed performance of each segment of salespeople, when salespeople are incentivized based on $0.5A + 1.5M$ in Table 8 to compare profitability of multiplicative versus additive incentive plan.

Similarly, to find the comparable incentive plan of specialized salespeople in the second counterfactual simulation (job task allocation), we need to find profit-maximizing multipliers on A (k^A) for hunters and

Figure OA2   Grid Search to find Profit-Maximizing Additive Aggregation Plan

$(Bonus = wA + (2 - w)M)$
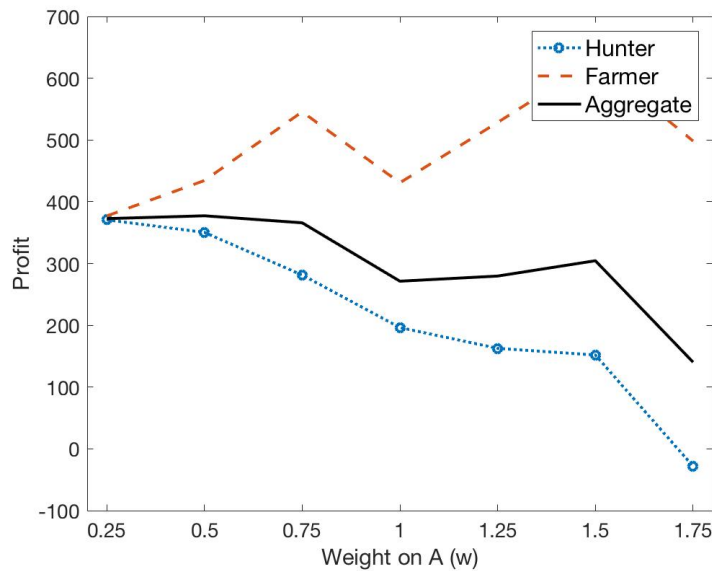
M (k^M for farmers. Under low k^A and k^M, on one hand, the firm would incur lower cost than under high k^A and k^M, because smaller incentives are paid out to the salespeople. On the other hand, hunters are less incentivized to bring in new loans and farmers are less motivated to collect past loans. Such trade-off between cost and benefit under different values of k^A and k^M makes it an empirical problem to find the profit-maximizing points of k^A and k^M. We numerically solve for the profit-maximizing multipliers by grid search over k^A and k^M. Figure OA3 compares firm profits (Net Present Value of loans - Incentive Payout to salespeople) when $k^A \in \{0.25, 0.5, ..., 2.5\}$ and $k^M \in \{0.25, 0.5, ..., 2.5\}$ and finds that $k^A = 0.5$ and $k^M = 0.75$ generate the highest profit from specialized salespeople. When farmers' incentives are extremely low, e.g., $k^M = 0.25$, salespeople do not collect enough loans and end up generating negative profit. In Table 9, we compare profitability of multitasking versus specialized salespeople, when specialized salespeople are incentivized based on $0.75A$ (hunters) or $0.5M$ (farmers).

Figure OA3   Grid Search to find Profit-Maximizing Incentive Plan of Specialized Salespeople