Essays on Sales Management

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DISSERTATION ACCEPTANCE CERTIFICATE

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Essays on Sales Management

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Essays on Sales Management

Abstract

Sales management is one of the most important matters in marketing strategy. An effective sales management policy properly motivates and controls salespeople, thereby aligning their behaviors with the organization's objectives. This dissertation examines the implications of different sales management policies on salespeople's behaviors and, thus, their performance outcomes. The chapters consider two relevant topics on sales management: (i) the role of behavior-based vs. outcome-based sales force control measures and (ii) the effects of sales incentive design on customer relationship management.

The first chapter provides a dynamic structural analysis of sales agents' behavior in response to behavior-based and outcome-based sales force control measures. The analysis accommodates both observable, quantifiable sales effort (e.g., number of sales calls) and unobservable, qualitative sales effort (e.g., attitude), as well as the dynamics in demand induced by customer goodwill. The results show a trade-off between increasing the number of sales calls (behavior-based control) and offering additional incentives (outcome-based control); heterogeneous responses to reducing the level of price promotions; and how an organization can minimize the negative impact of reducing price promotions by utilizing different control measures.

The second chapter examines the role of incentive design as a lever to motivate customer-managing sales agents. The structural analysis considers four primary tasks associated with customer relationship management (CRM): acquisition, retention, cross-selling, and monetization. The findings demonstrate how providing additional incentives may create a negative spillover and decrease the performance of a substitute task; the long-term implications of incentive design; and how a multiplicative structure, a theoretically optimal contract for balancing effort, can serve as a double-edged sword.

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Introduction

The act of selling is an essential part of organizations' marketing activities and typically the only revenue-generating function therein. The sales profession in the United States involves around 15 million people, accounting for more than 10% of the labor force (U.S. Department of Labor, 2019). An average salesperson brings in a yearly revenue of \$10 million and \$8.8 million in the manufacturing and service sectors, respectively (Selling Power, 2019). Sales operation also involves significant costs. U.S. organizations dedicate more than \$800 billion each year to manage their sales force—an amount nearly four times the estimated \$208 billion spending on media and digital advertising (Zoltners et al., 2013; MAGNA, 2019). The significance of these figures indicate the importance of designing and implementing effective sales management policies for an organization to thrive.

Organizations administer various sales management policies in an attempt to boost their sales outcomes. Such policies, however, often prove unsuccessful or, sometimes, trigger outcomes that are less profitable, short-term oriented or even unethical, thereby harming the organization (Schweitzer et al., 2004; Zoltners et al., 2016). The success, or failure, of a sales management policy depends on how well organizations recognize their salespeople's underlying motives. Salespeople (or sales "agents") possess their own interests, which may not always align with those of the organization (or the "principal").

An effective sales management policy, therefore, provides adequate motivation such that salespeople's behaviors align with the organization's objectives.

The main challenge in sales management policy design arises because salespeople's behaviors, or sales "efforts," are unobserved in part or in full. Fully monitoring salespeople's behaviors, including soft skills such as attitude, professionalism, and communication ability, is very costly, if not impossible, in practice. Hence, organizations and researchers need to utilize observable measures, such as the number of sales calls and revenue generated, to infer salespeople's behaviors and thereby evaluate the effectiveness of various sales management policies. Doing so requires a behavioral assumption that connects the sales agent's motives with his or her observable actions and outcomes.

This dissertation presents two chapters that examine the causal implications of various sales management policies. Each chapter provides a unique dynamic structural model of sales agent's behavior in response to organization's control measures and incentive design. By using naturally occurring field data, which are based on actual behavior under a real-working environment, the models have practical applicability in the real world. Moreover, the structural formulation of the models allow evaluating various configurations of alternative management policies and thus provide insights on optimal sales strategy.

Chapter 1 examines the role of behavior-based and outcome-based sales force control measures for motivating heterogeneous salespeople. The model accommodates both observable, quantifiable sales effort (e.g., number of sales calls) and unobservable, qualitative sales effort (e.g., attitude), as well as the dynamics in demand induced by customer goodwill. The chapter aims to understand how multiple management levers—including incentives, route call planning and price promotions—jointly affect salespeople's behavior and thus performance outcomes in the short- and long-run. A series of counterfactual experiments demonstrate a trade-off between increasing the number of sales calls (behavior-based control) and offering additional incentives (outcome-based control); heterogeneous responses to reducing the level of price promotions in which some salespeople exert extra effort to mitigate the disadvantage; and how a firm can minimize the negative impact of reducing price promotions by utilizing different sales force control measures.

Chapter 2 investigates how sales incentive design influences customer-managing sales agents' behaviors and performance outcomes across multiple tasks. The analysis considers four primary tasks associated with customer relationship management (CRM): acquisition, retention, cross-selling, and monetization. The tasks are motivated under a multi-component incentive plan, which combines the performance outcomes into a pecuniary reward. By understanding the short- and long-term implications of sales incentive design, including structure (additive vs. multiplicative) and weight (incentive amount), the chapter offers insights on optimal CRM strategy. The results demonstrate how providing additional incentives may create a negative spillover and decrease the performance of a substitute task; and the long-term implications of incentive design. In addition, the study offers a unique contribution by showing how a multiplicative structure, a theoretically optimal contract for balancing effort, can serve as a double-edged sword. A poorly set goal on one task may spillover and demotivate all other tasks, causing the entire plan to fall short.

1

Managing Relational Sales: The Role of Behavior-Based and Outcome-Based Controls

1.1 Introduction

Salespeople act as the face of an organization. Some 15 million salespeople, in the United States alone, serve in a boundary role that connects the organization with its customers (U.S. Department of Labor, 2019). Salespeople take on multiple roles: interacting with current and potential customers, fulfilling their needs, and implementing promotional strategies for an organization's products and services. Furthermore, and especially in many business-to-business contexts, salespeople manage on-going relationships with customers as the organization's only source of direct contact. They make sales calls regularly to educate and promote the organization's products and services, thereby building customer goodwill toward the organization and, thus, maintaining long-term relationships. The impact of an organization's sales function is substantial. A single salesperson generates, on average, $10 million and $8.8 million in annual sales in the U.S. manufacturing and service industries, respectively (Selling Power, 2019). Hence, effective management of the sales force is the cornerstone for long-term growth and prosperity of sales-driven organizations.

To manage—monitor, direct, evaluate and compensate—salespeople's vast roles, organizations use various control measures that are either behavior-based or outcome-based (Anderson and Oliver, 1987).[1] An outcome-based control prioritizes the final outcomes or "results." Salespeople are held accountable for the objective and straightforward measures of performance (e.g., sales revenue, units sold, and quota attainment) rather than how they achieve them. This control measure involves limited supervising and managerial direction, thereby reducing the managerial overhead associated with monitoring salespeople. In sum, an outcome-based control is a laissez-faire policy, leaving salespeople to achieve the organization's desired outcomes using their own processes and tactics.

A behavior-based control, in contrast, addresses the selling "process" and involves considerable monitoring of salespeople's activities. The organization has a well-defined idea of what it wants the salespeople to do in order to achieve its desired outcomes, and its managers actively intervene and direct the operations of the salespeople. Sales results are presumed to follow in the long run rather than in the immediate future.

[1] Anderson and Oliver (1987) use the term "control systems" to conceptualize the overarching management philosophies. In this study, we use the term "control measures" to refer to specific management policies within a collective system.

Qualitative and more-complex input measurements (e.g., product knowledge, number of calls made, hours worked, customer survey response, and peer evaluation) are used to evaluate the sales force. Organizations choose behavior-based and/or outcome-based control measures to influence salespeople's behaviors, ideally in a way that they align with the objectives of the organization.

This study aims to understand how different control measures influence salespeople's motivation and, thus, performance in both the short and long run. By examining the role of different control measures, in conjunction with multiple sales management levers, this study addresses the following questions: What is more effective at improving sales: a mandatory increase in sales calls (behavior-based control) or providing a stronger incentive (outcome-based control)? What are the long-term outcomes of sales effort? How do control systems interact with other marketing instruments such as price promotions?

Examining the effectiveness of behavior- and outcome-based control measures poses three major challenges. The first challenge arises because sales agents' behavior, in part or in full, are costly to observe. Specifically, an agent's sales efforts consist of both quantifiable elements (e.g., number of sales calls, hours worked) that are readily observed and qualitative elements (e.g., attitude, passion) that are often unobserved, if not very costly to observe. An organization's inability to fully observe sales effort (i.e., hidden action) gives rise to agents' moral hazard. In modeling sales effort, existing studies have focused on either the observable quantity (Manchanda and Chintagunta, 2004; Mizik and Jacobson, 2004; Parsons and Abeele, 1981) or the unobservable quality (Chung et al., 2014, 2021a; Kim et al., 2021; Misra and Nair, 2011). However, without jointly examining the two different aspects of sales effort, a researcher may fail to fully capture the agents' moral hazard. For instance, when a firm mandates its salespeople to make more sales calls, they may simply increase the observable quantity at the sacrifice of the unobservable quality of calls. The issue become more complex as salespeople are heterogeneous and, thus, different control measures likely have differential effects across varying types of people.

Further complications emerge due to the dynamics from the customer side. In relational sales, customer behavior is often habitual (i.e., state-dependent) by which past sales history persists and affects current sales. Hence, organizations concentrate on making sales efforts that create long-lasting customer goodwill. Such inertia of customers, together with above moral hazard, also influences sales agents' behavior. For instance, given a highly loyal customer base, a salesperson may become less responsive to incentives or other control measures, since he or she can enjoy the spoils of customers' habitual buying.

The last challenge arises when other management levers, such as price promotions, are considered in conjunction with the control measures. Acting in their own interest, salespeople's behavior becomes intertwined with the organization's management policy and, as a result, may yield unintended consequences. For example, when the organization offers price discounts on its products, salespeople can take this into account and decide to shirk, thereby exerting less sales effort. Therefore, we need to carefully infer salespeople's behavior to fully understand the implications of different control measures and their interaction with other management levers.

This study formulates a dynamic structural model of sales force behavior in response to behavior- and outcome-based control measures. The model formally disentangles the observable and unobservable elements of sales effort and considers many of the key elements involved in relational sales: frequency of sales calls, quality of sales effort, dynamics of customer goodwill, agent's ability, and the effectiveness of price promotions. The study's comprehensive model helps organizations better understand their salespeople's response to different control measures and, thus, provides guidance on the optimal design of compensation structure, call planning, and price promotion policies.

The analysis reveals existence of different types of salespeople that possess heterogeneous behavior. A series of counterfactual experiments shows ways in which salespeople's actions and performance change with alternative compensation, call planning, and promotion policies. The results demonstrate a trade-off relation between imposing a stricter call plan (behavior-based control), which mandatorily increases the frequency of sales calls, versus providing a stronger incentive (outcome-based control); the potential consequences, yet with an unexpected advantage, of reducing the level of price promotions; and how combining reduced promotions with extra incentives can effectively offset the loss in revenue.

The remainder of the paper's structure is as follows. Section 1.2 summarizes the related literature. Section 1.3 describes the institutional settings. Section 1.4 presents the model. Section 1.5 describes the estimation procedure and identification. Section 1.6 presents the estimation results and the counterfactual analyses. Section 1.7 concludes.

1.2 Related Literature

This study is related to several streams of research on sales management. First and foremost, this study relates to the research on sales force control.[2] The foundational work by Anderson and Oliver (1987) conceptualizes the two approaches toward sales force control systems. Outcome-based control holds salespeople accountable for their own tangible results. Organizations take this approach to provide an equitable measure for

[2] Sales force control, in a broad sense, corresponds to sales force management. Here, we focus on the stream of research addressing the implications of behavior-based and outcome-based control for its relevance to this study.

evaluation, keep salespeople's motivations intact, and reduce the managerial overhead. However, the emphasis on outcomes alone and inherent lack of direction trigger sales behaviors that are often short-term focused, outcome-only oriented, or sometimes even unethical, which may harm the organization (Schweitzer et al., 2004; Zoltners et al., 2016). Behavior-based control, in contrast, emphasizes the role of management direction and close monitoring of activities that lead to both tangible and intangible results. This approach helps execute long-term strategies and reduces the inequity that arise from events that are out of salespeople's influence. However, the drawbacks are that it is complex, subjective regarding evaluation, and difficult to collect the comprehensive behavior of salespeople (Anderson and Oliver, 1987; Challagalla and Shervani, 1996).

The theoretical studies on the topic, under the principal-agent framework of Hölmstrom (1979), primarily advocate the role of outcome-based control (i.e., incentives) in directing sales effort (Basu et al., 1985; Holmstrom and Milgrom, 1987; Rao, 1990; Lal and Srinivasan, 1993). By sharing the rewards with a salesperson in direct proportion to his or her measurable performance, the outcome-based control allows the organization to shift its risk to the salesperson. In these studies, behavior-based control (i.e., monitoring), once undertaken, reveals the agent's effort in full—and, thus, monitoring precludes the need for incentives. Consequently, the studies assume that the cost of monitoring is prohibitively high and rule out the role of behavior-based control. Joseph and Thevaranjan (1998) relax this assumption and allow partial monitoring of agent's behavior. The study finds that monitoring induces an inefficient allocation of agent's effort but, nonetheless, it may help organizations improve on profits by saving on compensation.

Most of the empirical work on behavior- and outcome-based control focuses on validating the conceptual framework of Anderson and Oliver (1987). The studies attempt to quantify the effectiveness of control systems on salespeople's behavior and performance (Ahearne et al., 2010; Challagalla and Shervani, 1996; Cravens et al., 1993; Jaworski and Kohli, 1991; Jaworski et al., 1993; Kohli et al., 1998; Krafft, 1999; Oliver and Anderson, 1994). Overall, the research suggests that behavior-based control measures are positively associated with salespeople's intrinsic motivation and commitment to the organization; however, some studies also find inconsistent or weak results on performance (Baldauf et al., 2005; Darmon and Martin, 2011). Such inconsistency is possibly due to limited data—the studies mostly rely on survey responses from sales managers and executives, which are subjective and imaginary.

This study's contribution to the stream of literature on sales force control is threefold. (i) It empirically verifies the role of different control measures using naturally occurring data. By examining the implications of different control measures based on actual behavior under a real-working environment, the study advances the literature in finding the true behavioral motives behind behavior- and outcome-based controls. (ii) The study's structural formulation allows testing of various configurations regarding behavior- and outcome-based control measures and, thus, provides guidance to organizations to foresee the effectiveness of changes in their management policies. Moreover, by analyzing the behavior and performance at the individual level, the study examines the differential implications of control systems across heterogeneous salespeople. (iii) This study evaluates the role of control measures in conjunction with other firm-level management levers, namely price promotions.

This study's empirical approach bears on the structural models of agents' behavior in response to various sales management instruments. To overcome the limited variation in sales management instruments, such as compensation structure and call scheduling policy, studies have turned their attention to the structural formulation of sales agents' behavior. Mainly, studies have utilized the variation in agents' motivation in response to their states—e.g., distance to quota (DTQ)—to infer unobserved effort from observed performance outcome. Existing studies, likely due to difficulties in data collection, focus their attention to compensation (Chung et al., 2014; Kim et al., 2021; Misra and Nair, 2011). More recently, studies are expanding their scope to investigate a number of policies beyond compensation, such as training, recruiting and termination, and shift scheduling (Chung et al., 2021a, 2022). These studies illustrate how multiple elements of sales management instruments jointly affect agents' behavior and, thus, an organization's sales performance.

The above studies, however, collect various elements of sales effort into a stylized, unidimensional object. They also limit to analyzing the short-term effectiveness of sales effort. To this end, this study contributes to the literature by disentangling the different elements of sales effort—quantity and quality. By disentangling and jointly examining the observed, quantifiable sales effort (e.g., sales calls) as well as the unobserved, qualitative (e.g., attitude) sales effort, the study demonstrates the inherent trade-offs in agents' decision making and, thus, broadens the understanding of agents' behavior. In addition, the model incorporates customer goodwill that persists over time, capturing the long-term effectiveness of sales effort.

By analyzing the role of sales calls—as an outcome of an agent's behavior—this paper also relates to the strand of literature on sales response models, namely, of sales-call (detailing) effectiveness. Early studies on the topic have generated mixed results, with elasticity measures ranging from a negative value of -14.8% (Parsons and Abeele, 1981) to overwhelmingly positive at 41% (Gönül et al., 2001). Mizik and Jacobson (2004), by addressing the endogeneity concerns latent in earlier studies, suggests that the sales-call effectiveness is relatively small. Manchanda and Chintagunta (2004) includes physician level heterogeneity in the response parameters to find that sales calls have positive effect on prescriptions with diminishing returns. Manchanda et al. (2004) finds evidence that physicians who are less responsive to detailing receive more frequent visits (compared to the more responsive ones), suggesting that the detailing policies used in practice may be suboptimal.

The above studies, however, treat sales calls as an exogenous decision of a firm rather than that of a salesperson. Hence, they are limited in capturing the behavioral motives of a salesperson in determining the number of sales calls—for instance, if a salesperson is short on, but has a reasonable chance to meet, the quota, that salesperson would likely make more frequent visits than someone who already achieved the quota or has no chance to do so. By allowing the number of sales calls to be part of an agent's decision, this study controls for the differential motives of salespeople; allows the call planning to interact with other management levers; and, thus, provides appropriate valuation of detailing visits. In addition, the structural approach of the study allows for causal analysis of alternative (counterfactual) policies, whereas descriptive studies limit this applicability.

1.3 Institutional Details

This section presents the institutional setting and data. The discussion proceeds in three parts: (i) sales environment, (ii) sales management and marketing instruments, and (iii) model-free evidence that stimulates model development.

The firm under study is a multinational generic pharmaceutical company, offering a portfolio of prescription products through its own direct sales force. The data come from the primary-care division of the firm's business operation in Turkey. Some notable

	Mean	S.D.
Monthly base salary (USD)	1,595.58	306.22
Annual variable pay (USD)	6,845.30	4408.11
Daily number of sales calls	15.26	2.06
Monthly promotional goods (% of sales)	27.87	6.61
Annual performance (sales/quota)	97.74	13.92
Meet annual quota (% of salespeople)	49.70	-
Number of salespeople	180	

Notes. Base salary and variable pay are in U.S. dollars. The numbers are approximate for confidentiality.

Table 1.1: Descriptive Statistics

aspects of the Turkish pharmaceutical market include: (i) the government regulates end-prices; (ii) competition is high among the generics companies because of the country's universal healthcare system,[3] and (iii) the country bans direct-to-consumer (DTC) advertising.[4] Consequently, personal selling in the form of sales calls plays a crucial role in the firm's go-to-market strategy. Thus, properly motivating and controlling the salespeople's activities are critical factors for success.

The data consist of salespeople's performance and number of sales calls, and the firm's price promotion policy from January 2015 to December 2016. To minimize the effect of the initial learning curve, we remove individuals less than or equal to six months since hire (i.e., who joined on or after July 2016). The data-cleaning process leaves us with 180 salespeople. Table 1.1 shows the corresponding descriptive statistics.

[3] Consumers are reimbursed up to 10 percent above the lowest priced (therapeutically equivalent) brand, which encourages the use of generics products.

[4] As of 2020, only Brazil, New Zealand and the United States allow DTC advertising.

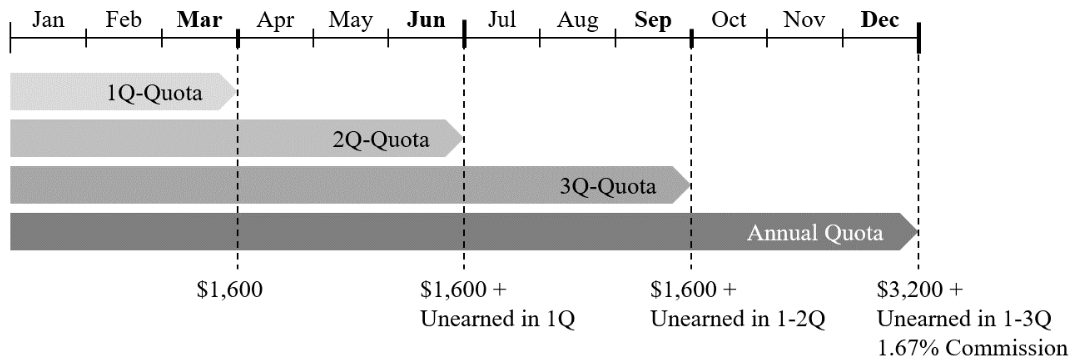
1.3.1 Sales Environment

The firm's sales process involves physicians at the front end and pharmacists at the back end. A physician prescribes the firm's product for the patient (end-consumer) to purchase—although, pharmacists can switch to a competitor's product (with the same generic molecules). Because physicians are not directly involved in the end-purchase process, their prescribing behavior is less sensitive to price and driven largely by relationships with the firm's salesperson—in the form of customer goodwill. After the physician writes a prescription, the pharmacists generates actual sales. They too, however, can affect sales by persuading patients to stay with or switch out of the prescribed product (across therapeutic equivalents). Because sales are directly linked to their revenue, pharmacists' behavior is highly influenced by price promotions.

In summary, physician prescription is important because, other things equal, sales do not occur without one. However, if the firm dedicates most of its resources toward physician detailing, competitors (with competitive price promotions) can convert the pharmacists to switch-out. Hence, balancing the sales resources toward both physicians, in the form of sales calls, and pharmacists, in the form of price promotions, is necessary for an ideal sales outcome.

1.3.2 Control Measures and Marketing Instruments

The following subsections discuss the firm's three primary instruments: compensation, call planning, and price promotions.



Notes. The amounts are converted to U.S. dollars. The numbers are approximate for confidentiality.

Figure 1.1: Compensation Structure

Compensation

The firm's compensation plan consists of base salary, quota-based bonus, and overachievement commission. In each month, salespeople receive a base salary of $1,600 on average. For the first three quarters, the firm gives a $1,600 bonus if a salesperson meets the respective quarterly quota. At the end of the year, the firm rewards a $3,200 bonus if a salesperson meets the annual quota and, in addition, provides an overachievement commission of approximately $135 (1.67% of the combined annual bonus) per any excess percentage points above the annual quota. The firm caps the amount of overachievement commission at $8,000, when a salesperson tops 160% of the quota. Figure 1.1 provides an overview of the firm's compensation plan, and Table 1.2 describes the quota-bonus payment schedule in detail.

The following two features of the compensation plan are noteworthy: (i) Quotas are cumulative from the beginning of the year. (ii) The firm defers the unearned bonus in each quarter to the subsequent quarter. For example, if a salesperson meets both Q1

	Q1	Q2	Q3	Q4
Performance (sales/quota)				
0 – 89.99 %	-	-	-	-
90 – 90.99 %	-	-	-	35 %
91 – 91.99 %	-	-	-	40 %
92 – 92.99 %	-	-	-	45 %
93 – 93.99 %	-	-	-	50 %
94 – 94.99 %	-	-	-	55 %
95 – 95.99 %	-	-	30 %	60 %
96 – 96.99 %	-	-	33 %	65 %
97 – 97.99 %	-	-	35 %	70 %
98 – 98.99 %	-	-	40 %	80 %
99 – 99.99 %	-	-	45 %	90 %
100 %	100 %	100 %	100 %	100 %
Greater than 100 %	100 %	100 %	100 %	101-200 %
Quota Evaluation Period	Jan-Mar	Jan-Jun	Jan-Sep	Jan-Dec
Bonus Amount	$1,600	$1,600 + unearned	$1,600 + unearned	$3,200 + unearned

Notes. The quarterly bonus amount is determined by multiplying the allocated bonus amount (bottom row) by the payout rate, respective to the performance (sales/quota) over the evaluation period.

Table 1.2: Quarterly-Bonus Payment Schedule

and Q2 quotas, he or she would receive $1,600 each in March and June. However, if a salesperson misses the Q1 quota and then meets the Q2 quota, he or she would receive $3,200 in June.

These features induce salespeople's forward-looking behavior and create unique dynamics. On the one hand, salespeople are motivated to keep up their pace throughout the year due to the deferral of unearned bonus amount. If a salesperson does not meet the quota in a quarter, his or her motivation to exert effort becomes greater (than had the person met the quota) because the total attainable bonus amount increases in the subsequent periods. On the other hand, poor performers may lose motivation and give up due the cumulative nature of the quota evaluation. The effect of negative sales in the early periods can last throughout the year, constantly demotivating the salespeople.

The firm uses an established consulting company to set and update salespeople's quotas. The quota-setting incorporates information about the salespeople's territories, such as market share, growth potential, and expected fluctuations in demand. This practice, by adjusting quotas based on objective information rather than on past sales performance, mitigates potential ratcheting concerns.

Call Planning

The firm operates its sales activity by route sales calls. Before the end of each month, every salesperson, together with the regional manager, creates a route-call plan for the upcoming month. The call plan includes a series of scheduled meetings with physicians in the salesperson's exclusive territory. During each month, salespeople make in-person calls following the assigned route and, if necessary, make extra calls to further promote the firm's products and improve the relationship with their physicians. On average, a salesperson makes 15 sales calls per day, where each call lasts for 5-10 minutes. During each meeting, the salesperson exerts effort to promote the firm's range of products.

Price Promotion

The government heavily regulates product prices. To gain competitive advantage under this constraint, pharmaceutical companies, including the focal firm, provide promotions in the form of free products, in proportion to sales quantity, to pharmacies. Each month, the firm sets its free-products policy, which outlines a distribution ratio by product. Hence, the firm's free-product policy, in a sense, is a form of price promotion. The salespeople do not have control over the ratio of free products, however, there is cross-sectional variation in the amount distributed—depending on the salesperson's product mix sold during the month. On average, a salesperson distributes 28% of products sold as free products. The free products are a critical component of pharmacies' revenues and, therefore, influence the pharmacist's decision to promote the firm's product over other generic equivalents.

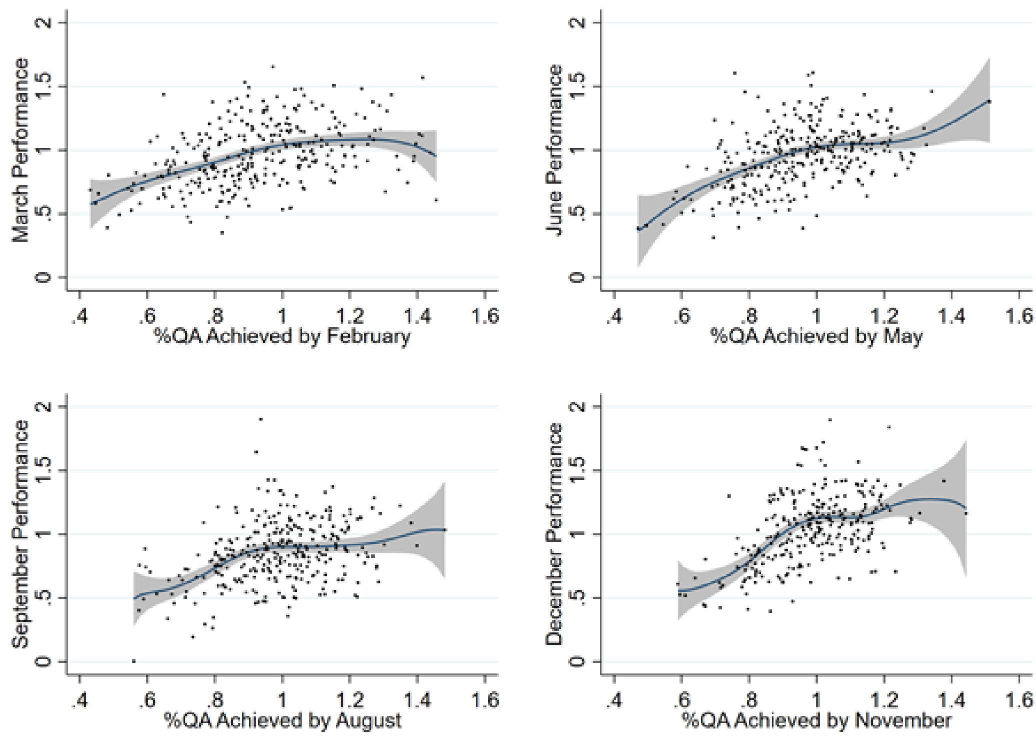
1.3.3 Model-Free Evidence

The following subsections discuss the model-free evidence on salespeople's forward-looking behavior, their decision variables, and long-term effectiveness of sales effort.

Forward-Looking Behavior

The relation between salespeople's performance and proximity to bonuses—distance to quota (DTQ)—provides evidence for forward-looking behavior (Steenburgh, 2008; Chung et al., 2014, 2021a). If agents are forward looking, their sales effort and, thus, performance would depend on the odds of reaching the quota and attaining the bonus. Moreover, the proximity to quota would affect only the behavior of agents with a reasonable chance of making the quota and not that of agents who are unlikely to meet the quota.

Figure 1.2 provides a graphical illustration of forward-looking behavior. The figure depicts the scatterplot and the best-fitting nonparametric smoothed polynomial of the salespeople's performance in bonus-payout months on the percentage of cumulative quota achieved (QA) until that month. Two observations are noteworthy from the figure: (i) From March through September, many salespeople with low QA achieve



Notes. The y-axis depicts performance (sales/quota) in the bonus-paying months; the x-axis shows the cumulative quota achieved (%QA) by the previous month.

Figure 1.2: Performance and Distance-to-Quota

performance above 100%. In December, however, only a few in the low-performing group does so. This is likely because the salespeople far from their quotas give up as they cannot recover the annual quota in just a month. (ii) Salespeople's effort, after gradually increasing in DTQ, flattens once the quota is met (i.e., when QA is above 100%). Hence, although the DTQ motivates the salesperson, such motivation decreases once he or she exceeds the quota.

Variable	Sales calls	Promotion rate
Intercept	**15.171**	**0.380**
	(0.078)	(0.003)
80%<QA<100%	**0.334**	0.008
	(0.127)	(0.005)

Notes. Dependent variable: number of sales calls or promotional free products rate. Standard errors are in parentheses. Significance at the 0.05 level appears in boldface.

Table 1.3: Sales Calls / Promotion Rate and Distance-to-Quota

Decision Variables

The institutional details in Sections 1.3.2 discussed how the number of sales calls is under salespeople's control but the rate of promotions is fixed by the firm (and, thus, exogenously given to salespeople). In this section, we verify the claims to determine the agents' decision set—i.e., are sales calls under agents' control and promotion rates indeed not so? To address this question, we turn to the idea that if a variable is under control by an agent, then it will likely depend on his or her DTQ—the agent will allocate more of the respective resource when needed to achieve the quota. Thus, by looking into how agents' DTQ influences the number of sales calls and the rate of promotions, we can determine the variables to include in modeling the agents' decision.

Table 1.3 depicts the relation between the DTQ and (i) the number of sales calls made and (ii) promotion rate distributed. The agents are split into two groups: those with QA between 80% and 100%; and those with QA below 80% or above 100%. The former group is short on quota and, thus, has the motivation to expend more resources, whereas the latter group is far away from or has already met the quota and, thus, has limited motivation. From the left column, we find evidence that the agents who are short on quota make extra sales calls to make up for their performance. However, this is not the case for the promotion rate, shown on the right column, that shows insignificant marginal increase for those short on the quota—implying that the agents do not have direct control over it.[5] The results confirm the institutional details in which salespeople determine their number of sales calls but not their rate of promotions. Hence, we include number of sales calls in the agents' decision set while leaving the promotion rate as a firm-level decision that is exogenously given to the agents.

Short- and Long-Term Effectiveness

Lastly, the determinants of customer goodwill—variables that have a long-lasting effect—are investigated. Table 1.4, column 1, shows the results of regression analyses with performance as the dependent variable and sales calls and promotion rates as explanatory variables. Intuitively, the two variables have positive and significant effects on contemporaneous sales. To understand the long-lasting effect, column 2 reports the regression results with lagged explanatory variables. The lagged number of sales calls is positive and significant, though with smaller effect size, indicating that its effect carries over time. The lagged promotions, however, is found insignificant. Hence, the results reveal that sales call effectiveness persists over time, creating goodwill that is long lasting, whereas promotion effectiveness is short lived.

[5] The result rules out the case in which the agents possess private information about the pharmacies' responsiveness to promotions and, as a result, make selective visits to those that favor the promotion rate set by the firm.

Variable	Performance	
	1	2
Sales calls	**0.007**	-
	(0.001)	-
Promotion rate	**0.608**	-
	(0.035)	-
Lagged sales calls		**0.003**
		(0.001)
Lagged promotion rate		0.029
		(0.037)
Fixed effects	Yes	Yes

Notes. Dependent variable: performance (sales/quota). Fixed effects controls for individual heterogeneity. Standard errors are in parentheses. Significance at the 0.05 level appears in boldface.

Table 1.4: Performance and Sales Calls / Promotion Rate

1.4 Model

This section presents a dynamic structural model of relational sales. The discussion proceeds in the following order: (i) the sales response function; (ii) the agent's per-period utility; (iii) evolution of state variables; (iv) the firm's compensation structure; and (v) dynamic allocation of the agent's sales effort. The agent's performance is determined by his or her sales effort, the firm's price promotion policy, and the amount of customer goodwill that the agent has generated in the past. The agent derives utility from compensation and disutility from making sales calls and enhancing their quality. Compensation is a nonlinear function of accumulated performance (e.g., quarterly sales). Hence, the agent exhibits forward-looking behavior and dynamically optimizes the sales efforts to maximize current and future payoffs.

1.4.1 Sales Response Function

An agent i in period t generates sales performance, q_{it}, as a function of a stock of customer goodwill, G_{it}, created by past sales effort; the number of sales calls, d_{it}; the quality of sales calls, e_{it}; price promotion, z_{it}; individual effect, α_i; and an idiosyncratic performance shock, ξ_{it}, such that

$$q_{it} = \exp\left(G_{it} + \delta d_{it} + e_{it} + \gamma z_{it} + \alpha_i + \xi_{it}\right). \tag{1.1}$$

The multiplicative form accounts for the dependence between quantity and quality of sales effort.[6] To account for both quantity and quality of sales effort, we include observed number of sales calls, d_{it} (hereafter, call frequency), and unobserved quality of sales calls, e_{it} (hereafter, call quality). For price promotion, z_{it}, we use the ratio of free products distributed—i.e., free-products/sales. The individual effect α_i represents the agent's baseline ability—i.e., performance attained without any sales effort. The distribution of the performance shock ξ_{it} follows $N(0, \sigma_\xi^2)$ and is known to the agent.

The stock-of-goodwill framework by Nerlove and Arrow (1962) provides a parsimonious yet effective measure to accommodate the long-term effect of sales efforts. The key concept is the formulation of an unobserved stock of goodwill, G_{it}, which is formed by a salesperson's past sales efforts and affects the current period outcome.[7] More for-

[6] The results are robust to an additive model structure. The additive setting reduces direct complementarity (in terms of performance) between call frequency and quality. However, indirect complementarity (in terms of motivation) between the two elements is still present when an agent is short on quota because an increase in one element helps the agent get closer to quota and, thus, increases the payoff from the other element.

[7] Formed by an agent's past sales efforts, customer goodwill can also be interpreted as the agent's learning by doing. Given agent-level performance data, the two effects are not distinguishable from each other. This paper attributes the effect to customer goodwill for two reasons: (i) The empirical setting (pharmaceutical detailing) involves sales calls that are routine and customers who are known to exhibit a high level of inertia. (ii) The data cleaning removes agents with

mally, the stock of goodwill G_{it} is specified to augment with past sales efforts, $d_{it}$and e_{it}, but to decay over time in the following geometric form:

$$G_{it} = \lambda\left(\delta d_{i,t-1} + e_{i,t-1}\right) + \lambda^2\left(\delta d_{i,t-2} + e_{i,t-2}\right) + \cdots = \sum_{j=1}^{\infty} \lambda^j\left(\delta d_{i,t-j} + e_{i,t-j}\right), \quad (1.2)$$

where λ is the carryover rate (and, thus, $1-\lambda$ is the decay rate). The long-term effect of sales efforts is captured using an infinite lag distribution. Combining Equations (1.1) and (1.2) yields an infinite distributed lag model:

$$q_{it} = \exp\left(\sum_{j=1}^{\infty} \lambda^j\left(\delta d_{i,t-j} + e_{i,t-j}\right) + \delta d_{it} + e_{it} + \gamma z_{it} + \alpha_i + \xi_{it}\right). \quad (1.3)$$

A straightforward application of Equation (1.3) is infeasible as it requires an infinite number of observations for the past sales effort. A practical approach to estimation is to substitute a part of the infinite-geometric sum in q_{it} using the lagged dependent variable $q_{i,t-1}$ such that

$$\begin{aligned} \tilde{q}_{it} &= \lambda \tilde{q}_{i,t-1} + \delta d_{it} + e_{it} + \gamma \tilde{z}_{it} + u_{it}, \\ u_{it} &= \tilde{\alpha}_i + e_{it} + \xi_{it} - \lambda \xi_{i,t-1}, \end{aligned} \quad (1.4)$$

where $\tilde{q}_{it} = \log\left(q_{it}\right)$, $\tilde{\alpha}_i = \left(1-\lambda\right)\alpha_i$, and $\tilde{z}_{it} = z_{it} - \lambda z_{i,t-1}$. The response function in Equation (1.4) captures the contemporaneous effect of agent's sales efforts (call frequency and quality) as well as their long-lasting effect. In the following section, we discuss how the agent dynamically optimizes the sales efforts.

less than or equal to six months of experience to minimize the effect of the initial learning curve.

1.4.2 Per-Period Utility

The agent's per-period utility (hereafter, utility) consists of positive pecuniary utility of compensation, W_{it}, and disutility from call frequency and call quality, C_{it}, such that

$$U(d_{it}, e_{it}, s_{it}) = \mathrm{E}_{\sigma_\xi}\left[W_{it}|d_{it}, e_{it}, s_{it}\right] - \gamma_i \mathrm{Var}\left[W_{it}|d_{it}, e_{it}, s_{it}\right] - C_{it}. \quad (1.5)$$

The amount of compensation, $W_{it} = W(q_{it}, s_{it}; \psi_{it})$, is determined by the agent's performance $q_{it} = q(d_{it}, e_{it})$ and state s_{it}, given the firm's compensation plan ψ_{it}. The pecuniary utility W_{it} takes the form of mean-variance utility, where $\gamma_i > 0$ represents the agent's risk preference. The agent incurs disutility $C_{it} = C(d_{it}, e_{it})$ from conducting sales calls d_{it} and enhancing the quality of those calls e_{it}. The disutility is convex in d_{it} and e_{it}, such that

$$C(d_{it}, e_{it}) = \exp(\theta_i^d + \varepsilon_{it}) \cdot d_{it}^2 + \theta_i^e \cdot e_{it}^2,$$

where θ_i^d and θ_i^e capture the disutility from call frequency (observed) and call quality (unobserved), respectively.[8] To account for the variation in observed number of calls, the associated disutility accommodates a structural error term ε_{it}, representing the states that affect the agent's call frequency decision but unobserved by the researcher. The structural error ε_{it} follows a normal distribution with location parameter zero and scale parameter σ_ε and is independently and identically distributed across agents and over time.

[8] The results are robust to allowing the disutility of call quality (e_{it}) to increase in proportion to the call frequency (d_{it}). The alternative setting induces stronger substitution between the two elements and, thus, amplifies their trade-off relation.

1.4.3 Evolution of State Variables

The agent's evolving state variables include four components: (i) the month type (MO), s_{it}^{MO}; (ii) the percentage of cumulative quota achieved (QA), s_{it}^{QA}; (iii) the percentage of annual bonus accrued (BA), s_{it}^{BA}; and (iv) the amount of customer goodwill (GW), s_{it}^{GW}.

The state transition occurs as follows:

1. Month type (MO)

$$s_{it}^{MO} = \begin{cases} 1, & \text{if } t \text{ is the start of the year,} \\ s_{i,t-1}^{MO} + 1, & \text{otherwise.} \end{cases}$$

2. Percentage of cumulative quota achieved (QA)

$$s_{it}^{QA} = \begin{cases} 0, & \text{if } t \text{ is the start of the year,} \\ \dfrac{s_{i,t-2}^{MO} \cdot s_{i,t-1}^{QA} + q_{i,t-1}}{s_{i,t-1}^{MO}}, & \text{otherwise.} \end{cases}$$

3. Percentage of annual bonus accrued (BA)

$$s_{it}^{BA} = \begin{cases} 0, & \text{if } t \text{ is the start of the year,} \\ \max\left\{ M_{t-1} \cdot R_{t-1}^{QB} \left(\dfrac{s_{i,t-2}^{MO} \cdot s_{i,t-1}^{QA} + q_{i,t-1}}{s_{i,t-1}^{MO}} \right), s_{i,t-1}^{BA} \right\}, & \text{otherwise.} \end{cases}$$

4. Amount of customer goodwill (GW)

$$s_{it}^{GW} = \lambda \cdot q_{i,t-1}.$$

The month-type evolves in a deterministic manner, whereas the latter three state variables evolve based on the agent's performance. The QA and the GW evolve every month, based on the performance in previous months; the BA evolves every quarter, based on receiving the quarterly bonus (the details of M_t and R_t^{QB} are provided in the next section). The QA and the BA are reset every January, whereas the GW evolves continuously without reset. The vector $s_{it} = s_{it}^{MO}, s_{it}^{QA}, s_{it}^{BA}, s_{it}^{GW}$ collects the evolving state variables.

1.4.4 Compensation

The agent receives compensation $W_{it} = W(q_{it}, s_{it}; \psi_{it})$ based on performance q_{it} and state s_{it}. Compensation W_{it} comprises three components: (i) monthly fixed salary F_{it}; (ii) quarterly bonus QB_{it}; and (iii) end-of-year overachievement commission OC_{it}, in the following form:

$$W_{it} = F_{it} + QB_{it} + OC_{it}.$$

The quarterly (and annual) bonus element QBit is as follows:

$$QB_{it} = \max\left\{M_t \cdot R_t^{QB}\left(\frac{(s_{it}^{MO} - 1) \cdot s_{it}^{QA} + q_{it}}{s_{it}^{MO}} - s_{it}^{BA}\right), 0\right\},$$

where M_t denotes the maximum attainable quarterly-bonus amount (including the deferred amount from previous periods) and R_t^{QB} represents the rate of quarterly bonus payout. More formally, the components M_t and R_t^{QB} are as follows:

$$M_t = \begin{cases} 1,600, & \text{if } s_{it}^{MO} = 3, \\ 3,200, & \text{if } s_{it}^{MO} = 6, \\ 4,800, & \text{if } s_{it}^{MO} = 9, \\ 8,000, & \text{if } s_{it}^{MO} = 12, \\ 0, & \text{otherwise,} \end{cases}$$

and

$$R_t^{QB} = \begin{cases} 0.30, & \text{if } 0.95 \leq s_{i,t+1}^{QA} < 0.96 \text{ and } s_{it}^{MO} = 9, \\ 0.33, & \text{if } 0.96 \leq s_{i,t+1}^{QA} < 0.97 \text{ and } s_{it}^{MO} = 9, \\ 0.35, & \text{if } 0.97 \leq s_{i,t+1}^{QA} < 0.98 \text{ and } s_{it}^{MO} = 9, \\ 0.40, & \text{if } 0.98 \leq s_{i,t+1}^{QA} < 0.99 \text{ and } s_{it}^{MO} = 9, \\ 0.45, & \text{if } 0.99 \leq s_{i,t+1}^{QA} < 1.00 \text{ and } s_{it}^{MO} = 9, \\ 0.35, & \text{if } 0.90 \leq s_{i,t+1}^{QA} < 0.91 \text{ and } s_{it}^{MO} = 12, \\ 0.40, & \text{if } 0.91 \leq s_{i,t+1}^{QA} < 0.92 \text{ and } s_{it}^{MO} = 12, \\ 0.45, & \text{if } 0.92 \leq s_{i,t+1}^{QA} < 0.93 \text{ and } s_{it}^{MO} = 12, \\ 0.50, & \text{if } 0.93 \leq s_{i,t+1}^{QA} < 0.94 \text{ and } s_{it}^{MO} = 12, \\ 0.55, & \text{if } 0.94 \leq s_{i,t+1}^{QA} < 0.95 \text{ and } s_{it}^{MO} = 12, \\ 0.60, & \text{if } 0.95 \leq s_{i,t+1}^{QA} < 0.96 \text{ and } s_{it}^{MO} = 12, \\ 0.65, & \text{if } 0.96 \leq s_{i,t+1}^{QA} < 0.97 \text{ and } s_{it}^{MO} = 12, \\ 0.70, & \text{if } 0.97 \leq s_{i,t+1}^{QA} < 0.98 \text{ and } s_{it}^{MO} = 12, \\ 0.80, & \text{if } 0.98 \leq s_{i,t+1}^{QA} < 0.99 \text{ and } s_{it}^{MO} = 12, \\ 0.90, & \text{if } 0.99 \leq s_{i,t+1}^{QA} < 1.00 \text{ and } s_{it}^{MO} = 12, \\ 1.00, & \text{if } 1.00 \leq s_{i,t+1}^{QA} \text{ and } s_{it}^{MO} \in \{3, 6, 9, 12\}, \\ 0, & \text{otherwise.} \end{cases}$$

By the structure of QB_{it}, the amount of bonus accrued (BA) in previous quarters, represented by s_{it}^{BA}, subtracts out the previously earned bonus from the maximum attainable amount M_t. Also note that in non-bonus periods, $QB_{it} = 0$ and, thus, the fixed salary F_{it} determines compensation W_{it} in whole. The overachievement commission OC_{it} (distributed only in December) is as follows:

$$OC_{it} = M_t \cdot R_t^{OC} \left(\frac{(s_{it}^{MO} - 1) \cdot s_{it}^{QA} + q_{it}}{s_{it}^{MO}} \right),$$

where M_t ($= 8,000$ for $s_{it}^{MO} = 12$) is the maximum attainable annual bonus as defined above and R_t^{OC} represents the rate of overachievement commission given by

$$R_t^{OC} = \begin{cases} 1.00, & \text{if } 1.00 \leq s_{i,t+1}^{QA} < 1.01 \text{ and } s_{it}^{MO} = 12, \\ 1.01, & \text{if } 1.01 \leq s_{i,t+1}^{QA} < 1.02 \text{ and } s_{it}^{MO} = 12, \\ 1.02, & \text{if } 1.02 \leq s_{i,t+1}^{QA} < 1.03 \text{ and } s_{it}^{MO} = 12, \\ 1.04, & \text{if } 1.03 \leq s_{i,t+1}^{QA} < 1.04 \text{ and } s_{it}^{MO} = 12, \\ & \vdots \\ 1.99, & \text{if } 1.59 \leq s_{i,t+1}^{QA} < 1.60 \text{ and } s_{it}^{MO} = 12, \\ 2.00, & \text{if } 1.60 \leq s_{i,t+1}^{QA} \text{ and } s_{it}^{MO} = 12, \\ 0, & \text{otherwise.} \end{cases}$$

The components M_t, R_t^{QB} and R_t^{OC} are common across all agents, while F_{it} varies depending on agent's tenure.[9] The vector $\psi_{it} = F_{it}, M_t, R_t^{QB}, R_t^{OC}$ collects the four components that represent the firm's compensation structure.

1.4.5 Dynamic Allocation of Actions

The course of agent's actions, compensation plan and state transitions naturally stimulate a dynamic structural model. An agent dynamically optimizes the call frequency d_{it} and call quality e_{it}, maximizing the sum of current and future payoffs. The value

[9] The model is applicable to a wide class of nonlinear compensation schemes beyond the illustrated institutional setting.

function is defined as the agent's discounted present value of the expected utility stream, such that

$$\begin{aligned}\tilde{V}(s_{it}) &= \mathrm{E}\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left\{\max_{d_{i\tau},e_{i\tau}} U(d_{i\tau},e_{i\tau},s_{i\tau})\right\}\Big| s_{it}\right]\\ &= \max_{d_{it},e_{it}}\left\{U(d_{it},e_{it},s_{it}) + \mathrm{E}\left[\sum_{\tau=t+1}^{\infty}\beta^{\tau-t}\left\{\max_{d_{i\tau},e_{i\tau}} U(d_{i\tau},e_{i\tau},s_{i\tau})\right\}\Big| d_{it},e_{it},s_{it}\right]\right\},\end{aligned}$$

where $U(d_{it}, e_{it}, s_{it})$ is the utility function in Equation (1.5) and β denotes the discount factor.[10] Hence, the agent makes an infinite sequence of optimal choices $(d_{i\tau}, e_{i\tau} : \tau = t, t+1, \dots)$ that determines the value of the expected utility flow. The expectation is taken with respect to the idiosyncratic performance shock $\xi_{i\tau}$ and the structural error $\varepsilon_{i\tau}$ for $\tau \geq t+1$.

The choice-specific value function, representing the discounted present value of choosing actions d_{it} and e_{it} is defined as:

$$V(d_{it},e_{it},s_{it}) = U(d_{it},e_{it},s_{it}) + \mathrm{E}\left[\sum_{\tau=t+1}^{\infty}\beta^{\tau-t}\left\{\max_{d_{i\tau},e_{i\tau}} U(d_{i\tau},e_{i\tau},s_{i\tau})\right\}\Big| d_{it},e_{it},s_{it}\right]. \tag{1.6}$$

In each period, the agent incorporates the information contained in his or her current states to evaluate the future outcome of actions: call frequency (d_{it}) and call quality (e_{it}).

The agent's call quality policy (i.e., optimal level of call quality), as a function of the

[10] The discount factor is fixed at $\beta = 0.95$.

state s_{it} and the number of sales calls d_{it}, is given by:

$$e_{it}^* = e(d_{it}, s_{it}) = \arg\max_e \{V(d_{it}, e, s_{it})\}$$

That is, the agent chooses the optimal level of call quality e_{it} that maximizes the discounted stream of expected utility flow, conditional on the current states and the call frequency. The agent's call frequency policy (i.e., optimal number of sales calls), as a function of the state sit is given by

$$d_{it}^* = d(s_{it}) = \arg\max_d \{V(d, e_{it}^*, s_{it})\}$$

The dynamic construction in Equation (1.6) illustrates two main trade-offs that govern the agent's behavior. First, the agent's disutility today from call frequency d_{it} and call quality e_{it} positively affects present and future payoffs. By the sales response function in Equation (1.4), the agent's actions d_{it} and e_{it} are stochastically linked to performance q_{it}. In turn, the performance outcome q_{it} (i) is directly linked to compensation W_{it} in bonus-paying periods; and (ii) indirectly affects future compensation by the evolution of state variables $s_{i,t+1} = f(q_{it}, s_{it}; \psi_{it})$, where $f(\cdot)$ collects the state transition discussed in Section 1.4.3. Second, the agent must allocate call frequency d_{it} and quality e_{it} within a desired disutility level. As salespeople typically are heterogenous in their interpersonal ability and relational skills related to sales efforts, the direction of the trade-off is not obvious and may differ by salespeople.

1.5 Estimation

This section presents the estimation procedure. In the first stage, we estimate the parameters of observable variables, apart from the structural parameters of agent preferences, using Generalized Method of Moments (GMM). The remaining structural parameters are then recovered in the second stage using Maximum Likelihood (ML).

1.5.1 Stage 1: GMM

In the first stage, we estimate the parameters governing the observed variables in the sales response function in Equation (1.4). The structure of the unobserved term $u_{it} = \tilde{\alpha}_i + e_{it} + \xi_{it} - \lambda\xi_{i,t-1}$ raises three challenges: (i) controlling for unobserved heterogeneity, $\tilde{\alpha}_i$; (ii) addressing the endogeneity problem caused by correlation between lagged dependent variable, $\tilde{q}_{i,t-1}$, and unobserved heterogeneity, $\tilde{\alpha}_i$; and (iii) addressing the serial correlation induced by the lagged idiosyncratic shock, $\lambda\xi_{i,t-1}$.

The dynamic panel data methods (Arellano and Bond, 1991; Blundell and Bond, 1998) provide a practical approach to tackle issues (i) and (ii). At the heart of the method is taking the first differences and utilizing the lagged dependent variables as instruments. To tackle issue (iii), we restrict the use of invalid moment conditions with regard to the lagged dependent variable (Chung et al., 2019; Hujer et al., 2005; Lee et al., 2017). More formally, the following moment conditions are used:

$$\mathrm{E}[\tilde{q}_{is}\Delta u_{it}] = 0,$$
$$\mathrm{E}[u_{it}\Delta\tilde{q}_{i,t-2}] = 0$$

for $t = 4, 5, \ldots, T$ and $s = 1, 2, \ldots, t-3$. The set of moment conditions are immune to the serial correlation in the error structure. In deriving the above, we use the fact that unobserved sales effort e_{it} within u_{it} is orthogonal to $\tilde{q}_{is}$ for $s = 1, 2, \ldots, t-1$ *conditional* on s_{it} per the state evolution discussed in Section 1.4.3. That is, past performance $\tilde{q}_{is}$ influences the agent's effort decision e_{it} only through the state evolution and, thus, conditional on states, the orthogonality condition for $\tilde{q}_{is}$ and e_{it} holds.

Regarding the number of sales calls and price promotions, we let the variables to be predetermined—the variables are correlated with past idiosyncratic shocks but not with current and future shocks. That is, the decisions on the call frequency (by the agent) and price promotions (by the firm) reflect past shocks, however, are made before current or future shocks are realized. The assumption leads to the following moment conditions:

$$
\begin{aligned}
&\mathrm{E}[x_{is}\Delta u_{it}] = 0, &&\text{for } s \leq t-2, \\
&\mathrm{E}[u_{it}\Delta x_{i,t-1}] = 0, &&\text{for } t = 3, 4, \ldots, T,
\end{aligned}
$$

where $x_{it} = \{d_{it}, z_{it}\}$. The main advantage of above dynamic panel data methods is that they yield unbiased estimates without having to rely on strictly exogenous instruments. Given unbiased estimates for λ, δ and γ, the next stage recovers the structural parameters of agent behavior.

1.5.2 Stage 2: ML

The second stage estimates the structural parameters of the utility and sales response functions. Using the utility function in Equation (1.5) and the choice-specific value function in Equation (1.6), one can obtain the expected value function $\mathrm{EV}(d, e, s)$ through the inner loop in the nested fixed-point algorithm (Rust, 1987). More specifically, the inner loop iterates over the following function:

$$
\begin{aligned}
&\mathrm{EV}(d_{it}, e_{it}, s_{it}) \equiv \mathrm{E}_{\varepsilon_{i,t+1},\xi_{i,t+1}}[V(s_{i,t+1})|d_{it}, e_{it}, s_{it}] \\
&= \int_{\xi_{i,t+1}} \int_{\varepsilon_{i,t+1}} \max_{d_{i,t+1}} \left\{ \max_{e_{i,t+1}} \{u(d_{i,t+1}, e_{i,t+1}, s_{i,t+1}) + \beta \mathrm{EV}(d_{i,t+1}, e_{i,t+1}, s_{i,t+1})\} \right\} d\varepsilon_{i,t+1} d\xi_{i,t+1}.
\end{aligned}
$$

Given the expected value function, one can infer the optimal level of call quality $e^*_{it}(d_{it})$, conditional on call frequency, by the level at which it maximizes $u(d_{it}, e_{it}, s_{it}) + \beta\mathrm{EV}(d_{it}, e_{it}, s_{it})$. Subsequently, the agent's choice probability of call frequency $\pi(d_{it})$, given states s_{it}, becomes

$$
\pi(d_{it}) = \Pr(d_{it}|s_{it}) = \phi_d \left(\frac{g(d_{it}) - g(d_{it} - \iota)}{d_{it}^2 - (d_{it} - \iota)^2} \right), \tag{1.7}
$$

where $g(d) = E[W(d)] - \gamma \mathrm{Var}[W(d)] - \theta^e e(d)^* + \beta\mathrm{EV}(d)$ and ι denotes some arbitrarily small constant. ϕ_d denotes the p.d.f. of a log-normal distribution with location and scale parameters θ^d and σ_ε , respectively.

The observed call frequency d_{it} and inferred call quality e_{it} enter the sales response function in Equation (1.4). Then, the likelihood of an agent's observations is computed by combining Equations (1.4) and (1.7). Given the T-period observation of the performance $\mathbf{q_i}$, number of sales calls $\mathbf{d_i}$, and state variables $\mathbf{s_i}$, the agent's likelihood becomes

$$
L_i(\Omega_i; \mathbf{q_i}, \mathbf{d_i}, \mathbf{s_i}) = \prod_{t=1}^{T} \varphi_\xi \left(\log(\hat{q}_{it}) - \log(q_{it})\right) \cdot \pi(\hat{d}_{it}),
$$

where the vector $\Omega_i = \{\theta^d_i, \theta^e_i, \sigma_\varepsilon, \gamma_i, \alpha, \sigma_\xi\}$ is the set of structural parameters; $\hat{d}_{it}$ is the observed number of sales calls, and $\hat{q}_{it}$ is the observed performance. φ_ξ denotes the p.d.f. of a normal distribution with mean zero and variance σ^2_ξ.

Agents belong to discrete segments, which accommodate unobserved and time-persistent heterogeneity (Kamakura and Russell, 1989). Let salesperson i belong to one of K segments $k \in \{1, \ldots, K\}$ with relative probabilities $m_k = \exp(\lambda_k)/\Sigma_{k'} \exp(\lambda_{k'})$ and denote the likelihood of parameters for salesperson i at time t, conditional on unobservable segment k, as $L_{ikt} = L(\Omega_k|k)$. Then, the likelihood of the segment-level parameters given the salesperson's history is

$$L_k(\Omega_k; \mathbf{q_i}, \mathbf{d_i}, \mathbf{s_i}) = m_k \left(\prod_{t=1}^{T} L_{ikt} \right).$$

The sum over the unobserved states $k \in \{1, \ldots, K\}$ yields the likelihood of salesperson i,

$$L(\Omega; \mathbf{q_i}, \mathbf{d_i}, \mathbf{s_i}) = \sum_{k=1}^{K} L_k(\Omega_k),$$

where $\Omega = \{\Omega_1, \ldots, \Omega_k\}$ contains the segment-level parameters. Finally, the overall log-likelihood over the N number of salespeople is

$$\sum_{i=1}^{N} \log \left(L(\Omega; \mathbf{q_i}, \mathbf{d_i}, \mathbf{s_i}) \right) = \sum_{i=1}^{N} \log \left(\sum_{k=1}^{K} m_k \left(\prod_{t=1}^{T} L_{ikt} \right) \right).$$

1.5.3 Model Discussion and Identification

This section discusses identification in the study's empirical context. The challenge in identifying the agent's utility function arises from limited variation in the firm's management instruments, namely the compensation contract. To facilitate identification under this restriction, we exploit the variation in an agent's sales performance (q_{it}) in response to his or her state variables (s_{it}). An agent likely devotes greater sales effort when he or she is close to meeting the quota (than when far from the quota) and, thus, the differences in sales performance at different distance-to-quota (DTQ) identify sales effort (Misra and Nair, 2011; Chung et al., 2014, 2021a). Within an agent's sales effort, the variation in performance, given DTQ and call frequency, identifies the unobserved call quality, which, in turn, identifies the associated disutility (θ^e). For instance, suppose that there are two agents with the same states and number of calls, but one shows higher performance than the other. This implies that the agent with higher performance has lower disutility of call quality (and, thus, exerts more effort on quality). The variation in observed number of sales calls given DTQ, identifies the disutility of call frequency (θ^d). Suppose that there are two agents with the same states, but one makes more frequent sales calls than the other. This implies that the agent with frequent sales calls has a lower disutility of call frequency. The within-agent variation in call frequency identifies the variance of the disutility shock (σ_ε). If a salesperson's call frequency does not change much with changes in states, this implies low variance in the disutility shock. The agent's performance in bonus-paying periods identifies risk preference (γ). A risk-averse agent would either over- or underachieve the quota to avoid compensation uncertainty, whereas a risk-neutral agent would perform on par.

Regarding the sales response function, the variation in previous-period performance, after accounting for possible endogeneity, identifies the long-term carryover rate (λ). The remaining sales response function parameters (δ and γ) are identified using the variation in the number of calls and price promotion rates. The agent's performance at the states under which the agent has no incentive to exert sales effort—i.e., when the agent is far below or above the quota—identifies the baseline ability (α). The variation in performance in the same states within an agent identifies the distribution of the performance shocks (σ_ξ).

Variable	Estimate
Sales response function	
Goodwill carryover, λ	**0.257**
	(0.028)
Sale calls, δ	**0.010**
	(0.003)
Promotion rate, ρ	**0.748**
	(0.057)
Fixed effects	Yes

Notes. Dependent variable: performance (sales/quota). Fixed effects controls for individual states. Standard errors are in parentheses. Significance at the 0.05 level appears in boldface.

Table 1.5: Stage 1. GMM Estimates

1.6 Results

This section discusses the results in the following order: (i) the parameter estimates of the model and their implications; and (ii) the counterfactual analyses that address the substantive questions of this study: how different control measures and marketing instruments affect behavior and performance.

1.6.1 Parameter Estimates

Tables 1.5 and 1.6 report the parameter estimates from stage 1 (GMM) and stage 2 (ML), respectively. Based on the Bayesian information criterion (BIC), the three-segment model shows the best fit for the ML.

From Table 1.5, we find that the long-term effect of sales effort—i.e., the carryover of customer goodwill—is 0.257. In the short-term, a unit increase in daily sales calls

Variable	Estimate		
	Segment 1	Segment 2	Segment 3
Utility function			
Disutility of call quality, θ^e	**21.603**	**19.938**	**5.431**
Disutility of call frequency			
Location, θ^d	**-7.202**	**-7.618**	**-8.016**
Scale, σ_d	**0.397**	**0.537**	**0.853**
Risk aversion, γ	0.001	0.002	0.001
Sales response function			
Baseline performance, α		**-0.659**	
S.D. of idiosyncratic shock, σ_ξ		**0.290**	
Segment size, λ	2.158	0.980	1.000

Notes. Significance at the 0.05 level appears in boldface. Standard errors are approximated by inverse of the Hessian of the log-likelihood and are omitted from the table for brevity.

Table 1.6: Stage 2. ML Estimates

and a 1 percentage point increase in free products lead to 1.04% and 0.75% increase in monthly performance, respectively.[11]

Regarding the structural parameters in Table 1.6, the disutility of call frequency and call quality range from -8.016 to -7.202 and 5.431 to 21.603, respectively. The disutility parameters are small for segment 3 (hereafter referred to as the high-performance type), representing the agents' ease and flexibility to engage in selling activities. The estimates are intermediate for segment 2 (hereafter referred to as the moderate-performance type) and are large for segment 1 (hereafter referred to as the low-performance type). The risk-preference is insignificant across the segments.

The share of the three segments and their descriptive characteristics are reported in Table 1.7. Segment 1, the low-performance type, has the largest share, 44.37%; segments

[11] The percentage changes are calculated using $\exp(0.0104) - 1$ and $\exp(0.0075) - 1$ to account for the log-transformed dependent variable.

Variable	Characteristic		
	Segment 1	Segment 2	Segment 3
Monthly base salary (USD)	1,578.88	1,584.39	1,658.31
Annual variable pay (USD)	5,291.19	7,471.17	9,065.61
Daily number of sales calls	14.58	15.86	15.66
Monthly promotional goods (% of sales)	28.09	28.66	25.76
Annual performance (sales/quota)	93.81	99.39	103.21
Meet annual quota (% of salespeople)	30.91	60.99	68.98
Segment size (%)	44.37	37.18	18.45

Notes. Base salary and variable pay are in U.S. dollars. The numbers are approximate for confidentiality.

Table 1.7: Segment Characteristics

2 and 3 represent smaller shares of 37.18% and 18.45%, respectively. Consistent with the parameter estimates in Table 1.6, segment 3 achieves the highest performance, with the largest portion meeting the annual quota. Segment 2, the moderate type, falls short on performance compared to segment 3 despite making similar number of sales calls. The low-performance type falls short in every performance dimension compared to the other segments.

1.6.2 Counterfactual Analyses

This section shows the results of counterfactual simulations that address the key substantive question of this paper: how can a firm better control its sales force behavior? The counterfactuals evaluate agents' performance and compensation expenditure according to changes in: (i) call planning, (ii) compensation, and (iii) price promotion policies. The counterfactuals suppose that the firm is undertaking its policy design at the beginning of 2017 (i.e., following the data observation period) with its portfolio of salespeople ($N = 180$). The basis for the changes is the current policy. For each new regime, we simulate 200 paths per each individual-segment pair using the parameter estimates of the model. Then, we allocate individuals into each segment based on segment probabilities. Finally, we aggregate performance and compensation.

Behavior-Based vs. Outcome-Based Control

A challenge in call plan design is to specify the amount of discretion to give to salespeople in determining the call frequency. Is it better to impose some mandatory number of calls, using behavior-based control measures? Or is it better to provide stronger incentives, as an outcome-based control measure, so that agents will voluntarily optimize their visits? To this end, the first counterfactual exercise examines the role of behavior-based control vs. outcome-based control on salespeople's behavior. Table 1.8 depicts the performance and compensation amount outcomes of the counterfactual simulations under the new regimes.

First, the behavior-based control imposes a mandatory increase in the number of daily sales calls by 1, 2, and 3 units (above the baseline) and keep everything else constant. Naturally, the call frequency increases—but the mandatory figure does not fully translate to the actual increase, since agents who nonetheless were to make extra calls (by their own needs) subsume such increase.

Overall, imposing a mandatory number of calls increases the salespeople's productivity. This raises an interesting question: if agents are indeed optimizing their behavior (under the outcome-based compensation structure), why does behavior-based control improve their performance? To understand the reason, recall that the agent's optimal decision depends on the net utility: positive monetary utility and negative disutility of sales effort. By being constrained to make additional calls, the salespeople's disutility

Panel (a) Behavior-Based Control: Call Planning

Counterfactual Simulation	Total	Within Segment		
		Segment 1	Segment 2	Segment 3
Increase daily calls by 1				
Annual performance	0.359	0.593	0.297	0.004
Call frequency	0.631	0.640	0.627	0.615
Call quality	-0.774	1.367	-1.199	-1.689
Compensation Amount	1.906	4.417	1.736	0.063
Increase daily calls by 2				
Annual performance	0.799	1.255	0.600	0.158
Call frequency	1.391	1.402	1.388	1.372
Call quality	-1.680	2.271	-3.093	-3.061
Compensation Amount	4.243	9.633	3.567	0.212
Increase daily calls by 3				
Annual performance	1.289	1.878	0.855	0.615
Call frequency	2.196	2.204	2.196	2.177
Call quality	-2.445	2.188	-5.600	-3.323
Compensation Amount	6.754	14.869	5.098	1.087

Notes. The change in average performance, call quality and compensation amount are in percentages; the change in call frequency are in numbers.

Table 1.8: Counterfactual Simulation #1: Behavior-Based vs. Outcome-Based Control

Panel (b) Outcome-Based Control: Incentives

Counterfactual Simulation	Total	Within Segment		
		Segment 1	Segment 2	Segment 3
Increase annual bonus by 5%				
Annual performance	0.524	0.359	0.485	0.854
Call frequency	0.023	0.027	0.018	0.019
Call quality	3.902	4.821	3.542	3.596
Compensation Amount	2.688	3.429	3.100	1.815
Increase annual bonus by 10%				
Annual performance	1.041	0.716	0.942	1.707
Call frequency	0.045	0.053	0.034	0.039
Call quality	7.775	9.688	6.835	7.232
Compensation Amount	5.267	6.670	6.015	3.633
Increase annual bonus by 15%				
Annual performance	1.574	1.124	1.363	2.560
Call frequency	0.066	0.078	0.049	0.058
Call quality	11.738	15.232	9.807	10.855
Compensation Amount	7.988	10.504	8.690	5.462

Notes. The change in average performance, call quality and compensation amount are in percentages; the change in call frequency are in numbers.

Table 1.8 (Continued): Counterfactual Simulation #1: Behavior-Based vs. Outcome-Based Control increases, and their net utility remains lower than had the control measure not been imposed. Hence, despite the suboptimality from the salespeople's perspective, their overall performance and, thus, the amount of compensation they earn increase as a result of behavior-based control.

Another notable result is that, although the call quality decreases for the moderate- and high-performing groups, it actually increases for the low-performing group. For the salespeople in the former group, more frequent calls increase their productivity, which, in turn, reduces the marginal returns to call quality. Hence, the salespeople in the two groups reduce their quality of sales calls. Then, why do the salespeople in the low-performing group improve their call quality? This is because the performance improvement (as a result of additional calls) keeps these salespeople to be on track and prevents them from giving up. The resulting proximity to quota induces extra motivation and, thus, the group of salespeople improve their call quality. In sum, behavior-based control is more appropriate for the low-performing salespeople, reflected by the more pronounced increase in productivity.

Next, we increase the bonus amount by 5, 10, and 15% and keep everything else constant. Again, sales performance increases; however, there is a stark difference in behavior compared to the case of mandatory visits. The agents make limited increase in call frequency, but rather focus on call quality. Overall, it is the high-type segment that benefits the most from the policy.

The experiment demonstrates the trade-off between imposing behavior-based (call planning) vs. outcome-based (incentives) control measures. If the objective is to increase the morale of its low-performing salespeople, the organization may be better off by imposing behavior-based control measures such as mandatory increase in call frequency. Conversely, if the organization seeks to boost performance of the success-driven, high-

Counterfactual Simulation	Total	Within Segment		
		Segment 1	Segment 2	Segment 3
Increase daily calls by 3				
Annual performance	1.289	1.878	0.855	0.615
Call frequency	2.196	2.204	2.196	2.177
Call quality	-2.445	2.188	-5.600	-3.323
Compensation Amount	6.754	14.869	5.098	1.087
Increase annual bonus by 12.75%				
Annual performance	1.340	0.945	1.175	2.187
Call frequency	0.057	0.067	0.042	0.049
Call quality	9.991	12.817	8.488	9.248
Compensation Amount	6.785	8.814	7.490	4.662

Notes. The change in average performance, call quality and compensation amount are in percentages; the change in call frequency are in numbers.

Table 1.9: Counterfactual Simulation #1: Cost-Equivalent Policy Comparison

type salespeople, it should instead provide outcome-based controls such as stronger incentives.

Though the results shown in Table 1.8 provide a practical tool for evaluating the effectiveness of varying configurations of the two control measures, in practice, managers often seek for a policy that offers the best possible outcome under a budget constraint. As different policies entail different costs to implement, we normalize the cost factor (i.e., compensation amount) to conduct a cost-benefit comparison of different policies. The following analysis evaluates a scenario in which the allocated budget is aligned with that of increasing 1 call per day (i.e., approximately 1.90% increase in annual compensation). The case is equivalent to increasing the annual bonus by approximately 3.45%.

Table 1.9 depicts the relative effectiveness of corresponding policies: increasing the number of daily calls by 1 versus increasing bonus amount by 3.45%. Overall, the resulting performance is slightly higher when the firm increases its annual bonus. Similar to the above analyses, however, the target group of salespeople that are better motivated varies across the two policies. Increase in mandatory visits guide the low-type agents to perform better but its effect is limited for the high types, implied by the decreases in call quality. In contrast, incentives are more effective toward high-type agents, providing motivation to make better-quality sales calls and excel in performance.

Reducing the Level of Promotions

The next counterfactual simulation involves reducing the level of price promotions. The high-level of free products was a problem that the focal firm was facing at the time. To evaluate the consequences of price promotion on sales performance, we reduce its level by 5, 10, and 15%. Table 1.10 shows the results. As anticipated, sales performance decreases across all segments. However, we observe an unanticipated increase in sales effort—both call frequency and quality—as the salespeople try to offset some of the loss. Overall, the decrease in promotions harms the low-performance type the most, because they have the least amount of necessary skills and, thus, have a hard time selling without the added support.

Next, we try to recover the loss in performance using the two control measures: call planning and incentives. We find that by increasing the daily number of calls by 1 and increasing the bonus by 4.25% offsets the performance loss (i.e., net performance is close to zero) from reducing free products by 10%.

Table 1.11 shows that, similar to the above findings, call planning helps the low-type agents recoup their losses, while the high-type agents have limited gains. In contrast, when the firm increases the bonus amount, the high-type agents recoup their losses, though all three group of salespeople exert extra sales effort. In these two cases, however,

Counterfactual Simulation	Total	Within Segment		
		Segment 1	Segment 2	Segment 3
Reduce promotions by 5%				
Annual performance	-0.218	-0.287	-0.163	-0.142
Call frequency	0.003	0.002	0.004	0.003
Call quality	0.384	0.182	0.682	0.344
Compensation Amount	-1.191	-2.477	-0.915	-0.302
Reduce promotions by 10%				
Annual performance	-0.437	-0.575	-0.330	-0.282
Call frequency	0.005	0.003	0.008	0.006
Call quality	0.749	0.339	1.317	0.685
Compensation Amount	-2.374	-4.926	-1.848	-0.595
Reduce promotions by 15%				
Annual performance	-0.655	-0.860	-0.498	-0.423
Call frequency	0.007	0.004	0.013	0.009
Call quality	1.119	0.505	1.948	1.033
Compensation Amount	-3.555	-7.337	-2.816	-0.893

Notes. The change in average performance, call quality and compensation amount are in percentages; the change in call frequency are in numbers.

Table 1.10: Counterfactual Simulation #2: Level of Promotion

Counterfactual Simulation	Total	Within Segment		
		Segment 1	Segment 2	Segment 3
Reduce promotions by 10% + Increase daily calls by 1				
Annual performance	-0.059	0.045	-0.023	-0.277
Call frequency	0.636	0.644	0.635	0.620
Call quality	0.105	2.065	0.182	-0.963
Compensation Amount	-0.410	-0.408	-0.059	-0.634
Reduce promotions by 10% + Increase annual bonus by 4.25%				
Annual performance	0.018	-0.265	0.095	0.455
Call frequency	0.025	0.027	0.024	0.023
Call quality	4.110	4.498	4.383	3.771
Compensation Amount	-0.069	-2.058	0.894	0.967

Notes. The change in average performance, call quality and compensation amount are in percentages; the change in call frequency are in numbers.

Table 1.11: Counterfactual Simulation #2: Maintaining Performance Level

overall compensation decreases even with comparable performance outcomes. Hence, the experiments demonstrate how the firm can save on its overall compensation cost by combining the price-promotion policy with the two control measures. Further, the potential cost savings from reduced free-products distribution has yet to be accounted for and is an additional benefit that the firm can reap.

In summary, the results demonstrate that in order to reduce the burden on excess promotions, appropriate support is necessary to overcome the backfire from salespeople and their customers. Moreover, whether to use behavior-based vs. outcome-based control depends on the type of agents the firm wants to reinforce behavior. Overall, the analysis demonstrates the ability of the model to compare the effectiveness of various policies and conduct a cost-benefit analysis—and, thus, support organizations in determining the sales management policy that best suits their desired objective.

1.7 Conclusion

Designing and implementing an appropriate control measure, in a way that it aligns the salespeople's behavior with the objectives of the organization, is an important goal of sales organizations. By properly controlling their sales force, organizations induce greater sales effort from the salespeople while reducing the operating costs. This study develops and estimates a dynamic structural model of sales behavior in response to behavior-based and outcome-based control. To this end, the model incorporates various elements of relational sales: sales call frequency and quality, customer goodwill, agent's ability, and price promotions. The study investigates the role of multiple management levers, including compensation (outcome-based control), call planning (behavior-based control), and product promotions (marketing instrument), on influencing salespeople's behavior. Substantively, this paper helps organizations on (i) understanding the behavioral implications of different control measures; (ii) assessing the long-term outcomes of sales efforts; and (iii) evaluating the negative consequences of reducing price promotions—and how different control measures can be utilized to offset the losses. Collectively, this paper provides guidance to firms on the optimal design of their sales management policies.

Several important managerial implications emanate from the study's results. Imposing a stricter call plan (behavior-based control) that mandatorily increases the call frequency helps improve overall sales performance. By being constrained to make more calls, however, the quality of each sales call decreases for moderate- and high-performing salespeople. Interestingly, though, the low-performing salespeople's sales-call quality actually improves—because additional calls help them keep closer to their quotas and, thus, induce extra motivation. Overall, behavior-based control helps organizations support the low-type agents' productivity. In contrast, a stronger incentive (outcome-based control) raises sales effort across all salespeople, with the high-performing salespeople benefiting the most due to greater upside potential. In an effort to reduce excess operating costs, the focal firm steadily reduced its amount of promotional products distributed over time. We assume the firm maintains this practice, and experiment the consequences of reducing the level of price promotion. The results show that performance decreases across all segments. However, agents increase their sales effort—in an attempt to recoup some of their losses in compensation. Furthermore, by coupling reduced price promotion with other control measures, the firm can effectively save on the operating costs with minimal impact on performance.

This study has some limitations that open avenues for future research. First, our empirical setting does not allow price promotions to be part of the salespeople's decision making. In other sales domains, however, salespeople may be given authority over pricing and, thus, engage in bargaining or exhibit dynamic substitution across customers (Mishra and Prasad, 2004; Karlinsky-Shichor and Netzer, 2019). For instance, salespeople can provide lower prices when they are far away from quota and raise price once closer; and/or make trade-offs between ease of bargaining today and customers' lowered reference price tomorrow. Second, this paper considers the number of sales calls as a proxy for behavior-based control. However, recent advances in artificial intelligence and machine learning algorithms allow measuring and tracking unstructured individual behavior, which would help organizations enrich their application of other higher-level behavior-based control measures, such as mentoring and training. Finally, by using performance records at the salesperson level, this study does not consider heterogeneity in customer preferences. In practice, differences in customer behavior exist—for instance, some customers exhibit greater inertia while others are myopic—which may influence salespeople's behavior at a more micro level. Though not applicable in this paper's empirical setting, the aforementioned topics would provide exciting avenues for future research.

In summary, this study offers a rigorous and practical framework for understanding the role of behavior-based vs. outcome-based control measures on sales force behavior. The policy insights help organizations better understand the implications of their management levers—compensation, call planning, and price promotions. We believe that the study will guide sales organizations better control and motivate their sales force in ways that benefit both parties alike.

2

The Effects of Sales Incentive Design on Customer Relationship Management

2.1 Introduction

Salespeople connect customers with organizations. In doing so, they often take on multiple customer relationship management (CRM) responsibilities: establishing connections with potential customers, fulfilling various needs of existing customers, identifying new sales opportunities for up- and cross-selling, preventing customer defections, and maintaining a profitable customer portfolio. The diversity of tasks becomes more prominent in many business-to-business contexts, where salespeople take the role of an account manager, providing a one-stop solution to all the customer's needs. Salespeople's CRM tasks collectively foster the development of customer-organization relationships that are healthy and sustainable in the long run. In short, salespeople are de facto multitasking customer-relationship managers.

To control and motivate salespeople's multiple tasks, many organizations design an incentive plan that contains multiple components—each tailored to a different task. A survey of 400 sales organizations finds that more than 88% combine two or more performance components in their incentive plans—with the most-commonly used measures include sales revenue, account retention, number of new accounts, and customer satisfaction (WorldatWork, 2021).

Designing a multi-component incentive plan primarily involves determining its two primary attributes: (i) the *weight* and (ii) the *structure*. The weight attribute involves assigning quota levels and tying "reward amounts" to each component. It governs how challenging it is for salespeople to achieve each goal and, once achieved, how much reward they should receive. The weights determine the ratio of potential benefits that salespeople can achieve and, thus, the relative strength of motivation across different tasks. For an incentive plan to function as desired, organizations should attach appropriate incentive amount to each task so that their motivational role remains intact.

The structure attribute involves choosing between "additive and multiplicative form" for combining multiple components. It determines how component-wise rewards are consolidated into a total reward. The theory finds that an additive structure is more applicable when the underlying tasks are independent (MacDonald and Marx, 2001). Under an additive structure, salespeople view the tasks as substitutes and exert greater efforts toward the tasks that they are relatively efficient at. In contrast, a multiplicative structure is adequate when an organization prefers salespeople's efforts to be spread across different tasks. This structure mitigates potential adverse specialization—focusing on one's specialty and neglecting others—caused by an additive structure and directs salespeople to balance their efforts across the associated tasks.

The weight and structure of a multi-component incentive plan collectively determine salespeople's degree of motivation and, thus, performance outcomes across multiple CRM responsibilities. However, crafting an effective incentive plan is challenging. Nearly 80% of U.S. sales organizations revise their incentive plan every two years or less (Zoltners et al., 2012), which attests to the challenges and demonstrates the prevalence of malfunctioning incentives plans in practice.

This study aims to understand how sales-incentive design affects salespeople's behavior and, as a result, their performance outcomes across various CRM tasks. By examining the implications of different incentive weights and structures, the study addresses the following research questions: What is more effective at motivating salespeople: an additive structure or a multiplicative structure? What are the benefits and risks of each structure? How do relative weights on incentive components interact with the structure? What are the short- and long-term consequences of incentive design on a firm's CRM strategy?

There are three major challenges to understanding salespeople's behavior in response to a multi-component incentive design. First, a multi-component incentive plan, by design, involves arranging multiple tasks, weights, and structures into a collective system. Because organizations typically adjust multiple components during their plan redesign, a ceteris paribus evaluation of a component change using a quasi-experimental design is limited. A researcher may consider a fully controlled field experiment to tease out a treatment effect. However, conducting a series of experiments across many possible combinations of weights and structures are difficult, if not impossible, in practice. Furthermore, even if such a large number of experiments were possible, an incentive plan is a system in which multiple components are intertwined; thus, an effect of a component change under one incentive design will likely have different implications under alternative arrangements.

Second, a researcher does not directly observe salespeople's multi-dimensional efforts; but only indirectly through the performance outcomes correlated with the efforts. For multitasking salespeople, the underlying tasks are interdependent—some substitute, while others complement one another—per the incentive plan. Hence, salespeople consider such dependence when allocating their unobserved efforts. Therefore, a behavioral assumption on salespeople's preferences—how they value the disutility of multi-dimensional efforts—is necessary to link their financial motives to performance outcomes.

Third, CRM metrics are often dynamic. Salespeople's efforts today (e.g., an increase in acquisition) may persist and affect their performance outcomes tomorrow (e.g., a greater opportunity to cross-sell). Salespeople, knowing this, dynamically adjust their efforts to invest for the future (by increasing effort) or harvest from the past (by decreasing effort). Failure to account for such dynamics may bias the disutility of effort and, thus, the behavioral model needs to endogenize the dynamics surrounding CRM metrics. In addition, the dynamics may cause performance outcomes to vary over time, which may obscure long-term outcomes. Hence, for complete inference, a researcher should recognize both the short- and long-term effectiveness of incentive design.

To address these challenges, this study formulates a dynamic structural model of a sales agent's behavior in response to a multi-component incentive plan. We collaborate with a major micro-finance institution, which assigns its salespeople four CRM responsibilities: acquisition, retention, cross-selling, and monetization. The firm operates a multi-component incentive plan that combines additive and multiplicative structures. Using naturally occurring field data on salesperson-level performance, we investigate the short- and long-term implications of sales incentive design.

A series of counterfactual simulations demonstrate the interrelated nature of multitasking salespeople's behaviors and how changes in incentive design leads salespeople to reallocate their efforts across tasks. The findings offer the following managerial implications: (i) Providing additional incentives may not always prove beneficial. The increase may create a negative spillover and decrease the performance of a substitute task. (ii) An organization short on budget but wanting to promote a certain CRM task can achieve its goal by wittingly creating a negative spillover through de-incentivizing a substitute task. (iii) The dynamics of CRM metrics may generate long-term outcomes that are not readily observed. (iv) Organizations should take extra caution when designing a multiplicative structure. The lack of motivation caused by an ill-conceived multiplicative component may dampen all connected outcomes because of negative spillover.

The findings offer unique contributions to the literature on multitasking salespeople and multi-component incentives (MacDonald and Marx, 2001; Kim et al., 2021; Chung et al., 2021b). The multiplicative structure, a theoretically optimal contract for balancing effort and preventing adverse specialization, can serve as a double-edged sword. To balance various efforts, the structure imposes a high degree of integration across tasks and its success hinges on appropriate weight being tied to the focal task. However, if the weight is inadequate, the negative effect spills over and demotivates all of the remaining tasks—thereby causing the entire plan to fail.

The remainder of the study is organized as follows. Section 2.2 describes the institutional setting and provides model-free evidence that facilitates the model. Section 2.3 presents the dynamic structural model of a multitasking sales agent. Section 2.4 presents the results and counterfactual analyses that address the key questions of this study. Section 2.5 concludes.

2.2 Empirical Setting

This section discusses the institutional details and data, the firm's multi-component incentive structure, and descriptive evidence that justifies model development.

2.2.1 Institutional Details and Data

The focal firm is one of the largest microfinance institutions (MFI) operating in Latin America, with more than 12,000 employees in 500 offices serving its 2.5 million customers as of 2018. The firm offers a portfolio of banking services, including individual-credit loans, group-credit loans, insurance products and savings accounts, through its own direct sales force.

The data come from the firm's individual-credit-loan division in Mexico. The main customer base is small- and medium-sized enterprises (SMEs), which serves as the backbone of the local economy.[1] The SMEs in Mexico, due to their remote locations and informal operations, have limited access to established brick-and-mortal financial services. Consequently, the firm's go-to-market and CRM strategies considerably depend on door-to-door personal selling.

The firm's individual credit loans (hereafter, loans), on average, have a principal amount of \$1,500,[2] a year-long maturity period, and a monthly interest rate of 4.75% (an annual rate of 75%). The high interest rate reflects the firm's average loan-delinquency rate of 20% and is typical for an MFI, which provides credit-based loans—i.e., without any collateral—to customers with a limited credit profile. The firm's high average loan-

[1] In 2016, approximately 99.8% of the entire businesses in Mexico were SMEs, accounting for 52% and 72% of the country's gross domestic product (GDP) and employment, respectively.

[2] The monetary figures in this paper are approximate for confidentiality and are reported in U.S. dollars, converted using the exchange rate at the beginning of the data period (January 2016).

renewal rate of 48.7% indicates how it prioritizes the CRM activities carried out by the loan officers.

The loan officers (hereafter, salespeople) travel around in his or her territory to search for prospective customers, contact and interact with them, and support them during the loan-application process.[3] The salespeople also hold periodic meetings with active clients to reduce the delinquency risk,[4] facilitate renewal of the near-maturity loans, and to cross-sell insurance products. Hence, salespeople's CRM responsibilities include (i) acquiring new loans (acquisition), (ii) renewing existing loans at maturity (retention), (iii) cross-selling other financial products (cross-sell), and (iv) managing the portfolio risk to maintain healthy profitability (monetization).

The firm provides individual-specific quotas[5] on two performance metrics: (i) the number of loan renewals and (ii) the number of cross-sold products. The former quota is naturally derived from the number of loans maturing during the corresponding month. The latter is set using market-level information such as the number of existing clients and growth potential. The firm attempts to keep salespeople's motivation intact by updating the quotas objectively, rather than using past performance (commonly referred to as "ratcheting" the quota). Section 2.2.3 provides descriptive evidence on the effect of quotas on performance and the absence of quota-ratcheting.

The data consist of salespeople's monthly performance and quota history during an eleven-month period (February to December 2016). The performance records include

[3] The firm has full discretion on loan approval. For each application, the firm performs comprehensive risk-assessment and screening, based on verifiable borrower information such as business characteristics and credit history, to minimize potential risk. This setting contrasts with Kim et al. (2021) in which salespeople decide whether to approve the loans and thus are subject to moral hazard in the form of adverse loan selection.

[4] A loan is considered delinquent if its repayment is delayed for more than 8 days.

[5] The payout conditions within the incentive structure (see Section 2.2.2 for details) can also be interpreted as quotas that are common across all agents.

Metric	Mean	S.D.	Min	Max
Number of clients (N)	114.62	45.28	1	304
Performance				
Change in clients (A), #	0.29	4.99	-29	20
Loan renewals (R), #	4.81	3.54	0	23
Cross sales (C), #	7.79	5.55	0	34
Delinquency rate (M), %	4.60	4.95	0	100
Quota				
Loan renewals (Q^R), #	9.68	5.30	0	43
Cross sales (Q^C), #	11.51	6.15	0	44
Renewal quota attained (R/Q^R), %	48.32	24.81	0	100
Cross-sales quota attained (C/Q^C), %	66.72	30.64	0	200
Number of salespeople		672		
Number of observations		7,300		

Table 2.1: Summary Statistics

the number of clients in the portfolio, N; the change in the number of clients, A (*acquisition*),[6] the number of loan renewals, R (*retention*), the number of cross-sold insurance products, C (*cross-sell*), and the rate of delinquent loans in the portfolio, M (*monetization*). The two quotas on loan renewals, Q^R, and cross sales, Q^C, are also observed. To minimize the initial learning curve and because the firm's compensation plan applies to agents who have been with the firm for more than 180 days, the analysis focuses on those with a tenure of more than six months. After data cleaning, the final data set consists of 7,300 monthly observations across 672 salespeople.

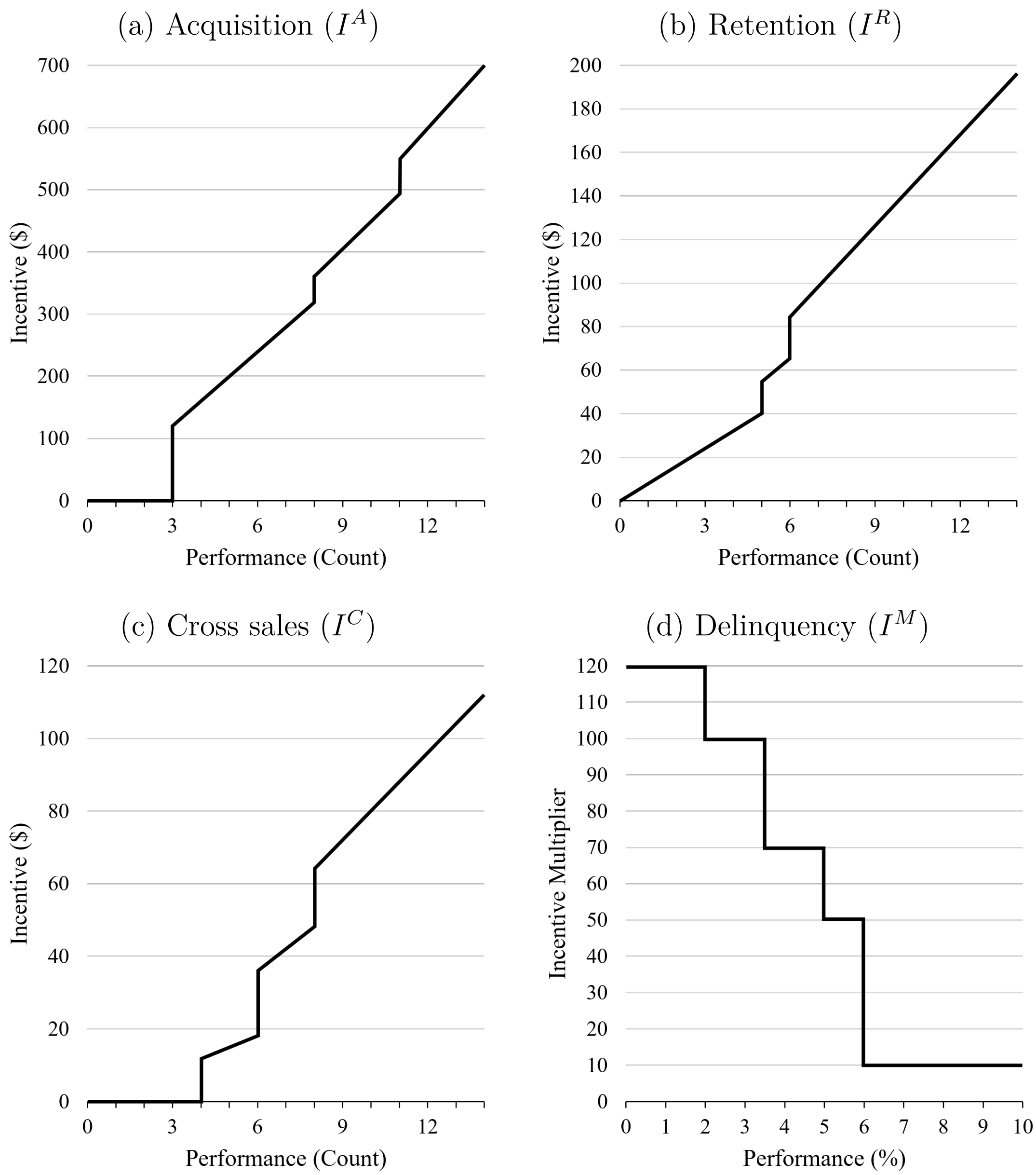
Table 2.1 provides summary statistics of the data. The salespeople, on average, oversee 115 clients, renew 5 loans, and cross-sell 8 insurance products each month. Out of their portfolio, 4.6% of the loans are delinquent with late payments each month. The average change in the number of clients is subtle, however, there exists heterogeneity

[6] Though we use the term acquisition for brevity, strictly speaking, the change in the number of clients captures the net outcome of customer acquisition and defect.

across agents in terms of customer acquisition and defect. On average, the salespeople achieve 48% of their renewal quotas and 67% of their cross-sales quotas.

2.2.2 Incentive Plan

The salespeople's incentive plan is multi-dimensionally designed around their four CRM responsibilities: (i) new loan acquisitions; (ii) existing loan renewals; (iii) cross-selling insurance products; and (iv) portfolio delinquency rate. The objective is to incentivize the first three performance outcomes and to discourage the last. During the data observation period, the firm administered a change in incentive structure in June 2016. Figure 2.1 illustrates an overview of the per-task incentive and Table 2.2 provides the specifics of each phase. For each of the four categories, the payout is determined by the respective performance condition. Then, the total incentive is calculated by adding or multiplying the category payouts.



Notes. The y-axis depicts the incentive amount (for acquisition, retention, and cross sales) and incentive multiplier (for delinquency). Combined incentive amount is calculated by $(I^A + I^R + I^C) \times I^M$. The x-axis depicts performance in numbers (for acquisition, retention, and cross sales) and percentages (for delinquency). The monetary figures are converted to U.S. dollars. The numbers are approximate for confidentiality.

Figure 2.1: Incentive Structure

Panel (a): Structure #1 (February – May 2016)								
Category	Acquisition (A)		Renewal (R)		Cross sales (C)		Delinquency (M)	
Incentive	Condition	Payout (I^A)	Condition	Payout (I^R)	Condition	Payout (I^C)	Condition	Payout (I^M)
	$A \leq 2$	\$0	$R/Q^R < 50\%$	$\$8 \times R$	$C/Q^C < 40\%$	\$0	$M \leq 2\%$	120%
	$3 \leq A \leq 7$	$\$40 \times A$	$50\% \leq R/Q^R < 60\%$	$\$11 \times R$	$40\% \leq C/Q^C < 60\%$	$\$3 \times C$	$2\% < M \leq 3.5\%$	100%
	$8 \leq A \leq 10$	$\$45 \times A$	$60\% \leq R/Q^R$	$\$14 \times R$	$60\% \leq C/Q^C < 80\%$	$\$6 \times C$	$3.5\% < M \leq 5\%$	70%
	$11 \leq A$	$\$50 \times A$			$80\% \leq C/Q^C$	$\$8 \times C$	$5\% < M \leq 6\%$	50%
							$6\% < M$	10%
Calculation	$(I^A + I^R + I^C) \times I^M$							
Panel (b): Structure #2 (June – December 2016)								
Category	Acquisition (A)		Renewal (R)		Cross sales (C)		Delinquency (M)	
Incentive	Condition	Payout (I^A)	Condition	Payout (I^R)	Condition	Payout (I^C)	Condition	Payout (I^M)
	$R/Q^R < 55\%$	$\$28 \times A$	$R/Q^R < 55\%$	$\$6 \times R$	$C/Q^C < 50\%$	\$0	$M \leq 2\%$	120%
	$55\% \leq R/Q^R < 65\%$	$\$56 \times A$	$55\% \leq R/Q^R < 65\%$	$\$48 \times R$	$50 \leq C/Q^C < 70\%$	$\$3 \times C$	$2\% < M \leq 4\%$	100%
	$65\% \leq R/Q^R$	$\$78 \times A$	$65\% \leq R/Q^R$	$\$50 \times R$	$70\% \leq C/Q^C$	$\$6 \times C$	$4\% < M \leq 6\%$	70%
							$6\% < M$	30%
Calculation	$(I^A + I^R + I^C) \times I^M$							

Notes. The monetary figures are converted to U.S. dollars. The numbers are approximate for confidentiality. Total incentive is determined by adding/multiplying the category payouts. Each category payout is determined by the respective performance condition. For structure #2, acquisition payout I^A is distributed only if $A > 0$ (otherwise, $I^A = 0$). For agents with renewal quota $Q^R = 0$, the middle condition ($\$200 \times R$ for structure #1 and $\$850 \times R$ for structure #2) is used for calculation.

Table 2.2: Incentive Structure

The structure during February to May 2016 (see Panel (a)), provides an independent (additive) payout for acquisition, renewal, and cross sales. The condition for acquisition payout (I^A) is determined by the absolute change in the number of clients, whereas the conditions for renewal (I^R) and cross-sales (I^C) payouts are determined by the performance relative to their respective quotas. The combined-three payouts then augment with the delinquency payout (I^M) in a multiplicative fashion. Such multiplier rewards low-portfolio risk and penalizes high-portfolio risk.

The incentive structure from June to December 2016 (see Panel (b)) introduces several modifications, most notable being a stronger emphasis on loan renewal. The renewal incentive payout has increased significantly for higher conditions, along with a stricter condition to fulfill. Perhaps more importantly, the condition for acquisition payout (I^A) now augments with the rate of renewal quota achieved (R/Q^R) rather than the acquisition performance (A) per se. Hence, generating a strong renewal outcome is a prerequisite for earning the acquisition incentive, as well as the renewal incentive. This also implies that, conversely, if one misses on the renewal performance, then the consequences spill over to harm the other incentive. The other changes under the second structure are relatively minor—the cross-sales incentive is weakened, and the delinquency penalty is eased. In summary, the structure change attempts to promote loan renewals, while slightly relaxing on the cross-sales and delinquency outcomes.

Table 2.3 provides an illustrative example of the incentive structure and calculation, with the focus on comparing the two structures. Let there be two agents: Agent A achieves 5 new loans and 3 renewals (strong-renewal scenario), and agent B achieves 7 new loans and 1 renewal (strong-acquisition scenario). Other performance and quota figures are identical between the two agents. Under the first structure, agent B benefits because of a strong acquisition incentive, despite the relatively low renewal incentive.

Conversely, if the performance outcomes are obtained under the second structure, it is now agent A who benefits from a strong renewal-quota achievement. However, the new structure proves detrimental for agent B, as his or her low renewal outcome holds back the acquisition incentive.

	Agent A				Agent B			
Category	Acquisition	Renewal	Cross sales	Delinquency	Acquisition	Renewal	Cross sales	Delinquency
Performance	$A = 5$	$R = 3$	$C = 2$	$M = 3\%$	$A = 7$	$R = 1$	$C = 2$	$M = 3\%$
Quota	-	$Q^R = 4$	$Q^C = 2$	-	-	$Q^R = 4$	$Q^C = 2$	-
Quota achievement	-	75%	100%	-	-	25%	100%	-
Structure #1 (February – May 2016)								
Category condition	$3 \leq A \leq 7$	$60 \leq R/Q^R$	$80\% \leq C/Q^C$	$2\% < M \leq 3.5\%$	$8 \leq A \leq 10$	$R/Q^R < 50\%$	$80\% \leq C/Q^C$	$2\% < M \leq 3.5\%$
Category payout	$I^A = \$40 \times A$	$I^R = \$14 \times R$	$I^C = \$8 \times C$	$I^M = 100\%$	$I^A = \$45 \times A$	$I^R = \$8 \times R$	$I^C = \$8 \times C$	$I^M = 100\%$
Calculation	(\$200 +	\$42 +	\$16)	$\times$ 1.00	(\$315 +	\$8 +	\$16)	$\times$ 1.00
Total incentive		\$258				\$339		
Structure #2 (June – December 2016)								
Category condition	$65\% \leq R/Q^R$	$65\% \leq R/Q^R$	$70\% \leq C/Q^C$	$2\% < M \leq 4\%$	$R/Q^R < 55\%$	$R/Q^R < 55\%$	$70\% \leq C/Q^C$	$2\% < M \leq 4\%$
Category payout	$I^A = \$78 \times A$	$I^R = \$50 \times R$	$I^C = \$6 \times C$	$I^M = 100\%$	$I^A = \$28 \times A$	$I^R = \$6 \times R$	$I^C = \$6 \times C$	$I^M = 100\%$
Calculation	(\$390 +	\$150 +	\$12)	$\times$ 1.00	(\$196 +	\$6 +	\$12)	$\times$ 1.00
Total incentive		\$552				\$214		

Notes. The monetary figures are converted to U.S. dollars. The numbers are approximate for confidentiality.

Table 2.3: Incentive Structure: An Illustrative Example

2.2.3 Descriptive Evidence

This section presents descriptive evidence on the long-term effect of acquisitions, the effect of quotas on performance outcomes, and the absence of quota ratcheting practice.

Long-Term Effects of Acquisitions

The institutional details in Section 2.2.1 discussed how a salesperson's number of existing customers (i.e., portfolio size) likely affects his or her CRM performance outcomes. For instance, a salesperson with a large customer base may have a greater potential to renew or to cross sell through periodic client meetings. However, such a large portfolio may, in turn, make it more difficult to acquire additional customers. Here, we seek to understand whether an agent's portfolio size, captured by the number of customers, affect his or her CRM performance outcomes and, if so, which ones. To address the question, we regress each of the four performance outcomes (acquisition, renewal, cross sales, and delinquency rate) on the number of customers by the beginning of the period.

Dependent variable	Acquisition (A)	Renewal (R)	Cross sales (C)	Delinquency (M)
Number of Clients (N)	−0.027***	0.030***	0.037***	0.0001
	(0.002)	(0.001)	(0.002)	(0.000)
Agent fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

Notes. Coefficients for agent and monthly fixed effects omitted for brevity. Standard errors, clustered at the agent level, are reported in parenthesis. * p<0.10; ** p<0.05; *** p<0.01.

Table 2.4: Portfolio Size and Performance

Table 2.4 shows the results of the regression analyses. The number of customers (N) has a negative and significant effect on acquisition performance (A), and positive and significant effects on renewal (R) and cross sales (C) outcomes. The results verify that, consistent with the previous discussion, agents' portfolio sizes indeed affect their performance outcomes. The finding also implies the countervailing dynamics embedded in agents' decision making—if an agent exerts his or her effort toward acquiring new customers today, the resulting increase in portfolio size may (i) reduce tomorrow's payoff by making acquisition more challenging and (ii) yield a greater payoff tomorrow from stronger renewal and cross-sales opportunities. To better understand such dynamics and their effects toward firms' CRM strategies, we include the number of customers in the agents' performance response functions.

Effect of Quotas on Performance Outcomes

This analysis examines the effects of renewal and cross-sales quotas on their respective performance outcomes. Table 2.5 shows the results of regression analyses with each of renewal (R) and cross sales (C) outcomes as the dependent variable and respective quotas (Q^R and Q^C) as the explanatory variable. The results show that the quotas each are positively and significantly correlated with their respective performance outcomes.[7] This implies that quotas serve as meaningful predictors for performance and, thus, we model agents' performance outcomes as a function of their respective quotas.

[7] The correlations can arise from a number of factors, e.g., the presence of quotas may serve as a strong motivator, and the quotas account for unobserved market characteristics that, in turn, also affect performance.

Dependent variable	Renewal (R)	Cross sales (C)
Renewal quota (Q^R)	0.475***	-
	(0.004)	
Cross-sales quota (Q^C)	-	0.682***
		(0.004)
Agent fixed effects	Yes	Yes
Month fixed effects	Yes	Yes

Notes. Coefficients for agent and monthly fixed effects omitted for brevity. Standard errors, clustered at the agent level, are reported in parenthesis. * p<0.10; ** p<0.05; *** p<0.01.

Table 2.5: Quota and Performance

Absence of Quota-Ratcheting Practice

In Section 2.2.1, we discussed how the firm updates the quotas in an objective manner as a means to maintain salespeople's morale. This section verifies the claims and shows evidence that quota-ratcheting practice (i.e., updating agent's quota based on his or her past performance) is not present under the current empirical setting. Table 2.6 reports the regression analyses for each of the two quotas, renewal and cross sales, as the dependent variable and lagged performance and lagged quota as the explanatory variable. The results find that the lagged performance variables are insignificant—implying the limited role of past performance on future quota updating—once the respective lagged quota, which serves as proxy for market potential, is controlled for. Hence, we treat quota updating as an objective firm-level decision that is exogenous to agents' performance outcomes.

Dependent variable	Renewal quota (Q^R)	Cross-sales quota (Q^C)
Lagged renewal (R_{t-1})	-0.049	-
	(0.026)	
Lagged renewal quota (Q^R_{t-1})	0.217***	-
	(0.018)	
Lagged cross sales (C_{t-1})	-	0.011
		(0.022)
Lagged cross-sales quota (Q^C_{t-1})	-	0.178***
		(0.020)
Agent fixed effects	Yes	Yes
Month fixed effects	Yes	Yes

Notes. Coefficients for agent and monthly fixed effects omitted for brevity. Standard errors, clustered at the agent level, are reported in parenthesis. * p<0.10; ** p<0.05; *** p<0.01.

Table 2.6: Ratcheting of Quota

2.3 Model

This section presents a model of sales agent's actions in response to the firm's incentive structure. Because of the dynamic nature of loan acquisition and retention, agents' actions de facto augment the firm's CRM strategy. The discussion proceeds in the following order: (i) performance response; (ii) per-period utility; (iii) evolution of state variables; (iv) firm's compensation structure; and (v) dynamic allocation of the agent's sales effort.

An agent's performance metrics—acquisition, retention, cross-selling, and profitability—are determined by his or her effort toward each task. The agent derives disutility from exerting such efforts and positive utility from compensation. Compensation is a non-linear function of the multi-dimensional performance. The effect of acquisition is long-lasting and, thus, the agent exhibits forward-looking behavior to maximize current and future payoffs.

2.3.1 Performance Response

Agent i's performance in period t comprises of four components: (1) change in the number of clients, A_{it} (acquisition); (2) the number of loan renewals, R_{it} (retention); (3) the sales of insurance products, C_{it} (cross-selling); and (4) the rate of delinquent loans, M_{it} (monetization). The following response functions determine the respective outcomes:

$$\begin{aligned} A_{it} &= -Q_{it}^R + e_{it}^A(s_{it}) + \alpha_1^A \cdot N_{it} + \xi_{it}^A, \\ \log(R_{it}+1) &= \log(e_{it}^R(s_{it})) + \alpha_1^R \cdot N_{it} + \alpha_2^R \cdot Q_{it}^R + \xi_{it}^R, \\ \log(C_{it}+1) &= \log(e_{it}^C(s_{it})) + \alpha_1^C \cdot N_{it} + \alpha_2^C \cdot Q_{it}^C + \xi_{it}^C, \\ \log(M_{it}+1) &= -\log(e_{it}^M(s_{it})) + \alpha_1^M \cdot N_{it} + \xi_{it}^M. \end{aligned} \tag{2.1}$$

The agent's multi-dimensional efforts toward acquisition e_{it}^A, retention e_{it}^R, cross-selling e_{it}^C, and monetization e_{it}^M positively affect the outcomes but accompany disutility (see Section 2.3.2 for details). The negative effort toward monetization reflects agent's desire to reduce portfolio delinquency rate. The portfolio size at the beginning of the period, N_{it}, augments with the agent's efforts to shift performance. In acquisition, A_{it}, the monthly renewal quota (i.e., the number of loans maturing in that month), Q_{it}^R, is subtracted to account for naturally occurring defect. For retention, R_{it}, and cross-selling, C_{it}, the applicable monthly quota Q_{it}^R and Q_{it}^C, respectively, act as additional performance shifters. The log-linear specification of R_{it}, C_{it} and M_{it} allows the agent's performance outcomes to be non-negative, consistent with the empirical setting.[8] The agent does not observe the idiosyncratic shocks $\xi_{it}^{(\cdot)}$ before making his or her effort decisions but is aware of their distribution, which follows $N(0, \sigma^2_{\xi,(\cdot)})$.

The performance response functions in Equation (2.1) associate the agent's unobserved efforts with observed customer metrics. The multi-dimensional outcomes collectively determine the agent's amount of compensation (incentive), which, in turn, determines his or her level of utility.

2.3.2 Utility

The agent derives utility based on compensation and multi-dimensional effort such that

$$\tilde{U}_{it} = \tilde{U}(e_{it}, s_{it}) = M(W_{it}|e_{it}, s_{it}) + C(e_{it}^A, e_{it}^R, e_{it}^C, e_{it}^M), \tag{2.2}$$

where $M(W_{it}|e_{it}, s_{it})$ is the positive pecuniary utility from compensation, W_{it}, and $C(e_{it}^A, e_{it}^R, e_{it}^C, e_{it}^M)$ is the disutility from exerting multi-dimensional effort.

The utility function in Equation (2.2) is ex-post in the sense that the performance shocks $\xi_{it}^{(\cdot)}$ in Equation (2.1), which affect the performance outcomes and thus compensation, are not realized at the time of agent's effort decisions. Hence, the agent makes his or her effort decisions based on the *expected* amount of compensation W_{it}, conditional on effort and his or her current states. This leads to the ex-ante utility function given by

$$U_{it} = U(e_{it}, s_{it}) = \mathrm{E}[M(W_{it}|e_{it}, s_{it})] - C(e_{it}), \tag{2.3}$$

where e_{it} collects the multi-dimensional effort into a vector, $e_{it} = \{e_{it}^A, e_{it}^R, e_{it}^C, e_{it}^M\}$.

[8] The log-transformation of efforts allow comparing their disutilities by normalizing the units.

The pecuniary utility M takes the form of logarithmic utility[9] such that

$$M(W_{it}|e_{it}, s_{it}) = \log(W_{it}|e_{it}, s_{it}),$$

where the vector of state variables s_{it} contains information related to compensation, including an agent's portfolio size as well as monthly quotas for loan renewal and cross-selling (see Section 2.3.3 for details).

The disutility C is convex in both (i) efforts associated with each task and (ii) combined effort such that

$$C(e_{it}) = \left\{\theta_i^A (e_{it}^A)^2 + \theta_i^R (e_{it}^R)^2 + \theta_i^C (e_{it}^C)^2 + \theta_i^M (e_{it}^M)^2\right\}^2,$$

where parameters $\theta_i^A, \theta_i^R, \theta_i^C$ and θ_i^M capture the disutility from acquisition, retention, cross-selling and monetization, respectively. The former convexity captures the diminishing returns to each task's effort and the latter convexity accounts for the interdependence of tasks under limited resources.

2.3.3 State Variables

The agent's state variables associated with compensation include three components: (1) the total number of clients, N_{it} (portfolio size); (2) monthly quota for loan renewals, Q_{it}^R (retention quota); and (3) monthly quota for insurance products, Q_{it}^C (cross-sell quota). The vector $s_{it} = \{N_{it}, Q_{it}^R, Q_{it}^C\}$ collects the three state variables.

Among the state variables, we model portfolio size to evolve over time—based on the

[9] The logarithmic utility implies constant relative risk aversion (CRRA) with the Arrow-Pratt measure of relative risk aversion $R_R(W) = 1$ (Arrow, 1971; Pratt, 1964).

descriptive analyses in Section 2.2.3—such that:

$$N_{i,t+1} = N_{it} + A_{it}.$$

The state evolution captures the dynamics surrounding present utility (associated with current-period compensation) and expected future utility (associated with later-period compensation). Exerting extra acquisition effort not only increases the probability of a larger acquisition bonus in the current period, but also affects future outcomes—either positively or negatively—because the portfolio size evolves based on the agent's acquisition outcome and, in turn, affects performance outcomes per Equation (2.1).

2.3.4 Compensation

The agent receives compensation $W_{it} = W(A_{it}, R_{it}, C_{it}, M_{it}|Q^R_{it}, Q^C_{it})$ based on performance outcomes conditional on quotas. Compensation W_{it} comprises of incentives associated with the four outcome categories: (1) acquisition incentive, I^A_t; (2) retention incentive, I^R_t; (3) cross-sales incentive, I^C_t; and (4) monetization incentive/discount multiplier, I^M_t. The structure of compensation is additive in the first three components and multiplicative in the portfolio risk in the following form:

$$W_{it} = (I^A_t + I^R_t + I^C_t) \cdot I^M_t.$$

More formally, the components I^A_t, I^R_t, I^C_t and I^M_t are as follows (illustrated based on February-May incentive structure):

1. Acquisition incentive: Payout is based on the change in the number of clients,

A_{it}.

$$I_t^A = \begin{cases} 0, & \text{if } A_{it} \leq 2, \\ A_{it} \times 40, & \text{if } 3 \leq A_{it} \leq 7, \\ A_{it} \times 45, & \text{if } 8 \leq A_{it} \leq 10, \\ A_{it} \times 50, & \text{if } 11 \leq A_{it}. \end{cases}$$

2. Retention incentive: Payout is based on loan renewals, R_{it}, relative to quota, Q_{it}^R.

$$I_t^R = \begin{cases} R_{it} \times 8, & \text{if } R_{it}/Q_{it}^R < 50\% \\ R_{it} \times 11, & \text{if } 50\% \leq R_{it}/Q_{it}^R < 60\%, \\ R_{it} \times 14, & \text{if } 60\% \leq R_{it}/Q_{it}^R. \end{cases}$$

3. Cross-sales incentive: Payout is based on insurance products sold, C_{it}, relative to quota, Q_{it}^C.

$$I_t^C = \begin{cases} 0, & \text{if } C_{it}/Q_{it}^C < 40\%, \\ C_{it} \times 3, & \text{if } 40\% \leq C_{it}/Q_{it}^C < 60\%, \\ C_{it} \times 6, & \text{if } 60\% \leq C_{it}/Q_{it}^C < 80\%, \\ C_{it} \times 8, & \text{if } 80\% \leq C_{it}/Q_{it}^C. \end{cases}$$

4. Monetization incentive/discount: Payout is based on the rate of delinquent loans, M_{it}.

$$I_t^M = \begin{cases} 120\%, & \text{if } M_{it} \leq 2.0\%, \\ 100\%, & \text{if } 2.0\% < M_{it} \leq 3.5\%, \\ 70\%, & \text{if } 3.5\% < M_{it} \leq 5.0\%, \\ 50\%, & \text{if } 5.0\% < M_{it} \leq 6.0\%, \\ 10\%, & \text{if } 6.0\% < M_{it}. \end{cases}$$

The category incentives I_t^A, I_t^R, I_t^C and I_t^M are common across all agents but varies over time as illustrated in Section 2.2.2.[10] The vector $\psi_{it} = \{I_t^A, I_t^R, I_t^C, I_t^N\}$ collects the four components that represent the firm's compensation structure.

2.3.5 Dynamic Allocation of Actions

The course of agent's actions, compensation plan and state transitions naturally stimulate a dynamic structural model. An agent dynamically optimizes multi-dimensional effort e_{it}, maximizing the sum of current and future payoffs. The value function is defined as the agent's discounted present value of the expected utility stream, such that

$$\begin{aligned}\tilde{V}(s_{it}) &= \mathrm{E}\left[\sum_{\tau=t}^{\infty} \delta^{\tau-t}\left\{\max_{e_{i\tau}} U(e_{i\tau}, s_{i\tau})\right\} \Big| s_{it}\right] \\ &= \max_{e_{it}}\left\{U(e_{it}, s_{it}) + \mathrm{E}\left[\sum_{\tau=t+1}^{\infty} \delta^{\tau-t}\left\{\max_{e_{i\tau}} U(e_{i\tau}, s_{i\tau})\right\} \Big| e_{it}, s_{it}\right]\right\},\end{aligned}$$

where $U(e_{it}, s_{it})$ is the utility function in Equation (2.3) and δ denotes the discount factor.[11] The agent makes an infinite sequence of optimal effort $(e_{it} : \tau = t, t+1, \dots)$ that maximizes the value of the expected utility flow. The expectation is taken with respect to the distribution of the performance shock $\xi_{i\tau}$ for $\tau \geq t+1$.

The choice-specific value function, representing the discounted present value of effort

[10] The components for June-December incentive structure can be derived analogously. The model is applicable to a wide class of nonlinear compensation schemes beyond the illustrated institutional setting.

[11] The discount factor is fixed at $\delta = 0.90$.

choice e_{it} is defined as:

$$V(e_{it}, s_{it}) = U(e_{it}, s_{it}) + \mathrm{E}\left[\sum_{\tau=t+1}^{\infty} \delta^{\tau-t} \left\{\max_{e_{i\tau}} U(e_{i\tau}, s_{i\tau})\right\} \middle| e_{it}, s_{it}\right]. \tag{2.4}$$

In each period, the agent incorporates the information contained in his or her current states to evaluate the future outcome of effort (e_{it}).

The agent's optimal effort policy is given by:

$$e^*_{it} = e(s_{it}) = \arg\max_{e} \{V(e, s_{it})\}$$

That is, the agent chooses the optimal level of effort e_{it} that maximizes the discounted stream of expected utility flow, conditional on the current states.

The dynamic construction in Equation (2.4) illustrates two main trade-offs that govern the agent's behavior. First, the agent's efforts incur disutility but positively affect present payoff. By the performance response functions in Equation (2.1), the agent's efforts e_{it} are stochastically linked to performance outcomes, A_{it}, R_{it}, C_{it} and M_{it}. The performance outcomes, in turn, are linked to compensation in the concurrent period. Second, the agent's acquisition effort e^A_{it} indirectly affects future payoff through the evolution of portfolio-size state, $N_{i,t+1} = N_{it} + A_{it}$. Thus, exerting extra acquisition effort not only increases the probability of a large acquisition bonus in the current period, but also affects future performance outcomes, $A_{i,t+1}$, $R_{i,t+1}$, $C_{i,t+1}$ and $M_{i,t+1}$, and thus future compensation.

2.3.6 Estimation

The estimation obtains the structural parameters of the utility and performance response functions. Using the utility function in Equation (2.3) and the choice-specific value function in Equation (2.4), one can obtain the expected value function $\mathrm{EV}(e, s)$ through the inner loop in the nested fixed-point algorithm (Rust, 1987). More specifically, the inner loop iterates over the following function:

$$\begin{aligned}\mathrm{EV}(e_{it}, s_{it}) &\equiv \mathrm{E}_{\xi_{i,t+1}}[V(e_{i,t+1}, s_{i,t+1})|e_{it}, s_{it}] \\ &= \int_{\xi_{i,t+1}} \max_{e_{i,t+1}} \{U(e_{i,t+1}, s_{i,t+1}) + \delta \mathrm{EV}(e_{i,t+1}, s_{i,t+1})\} \, d\xi_{i,t+1}.\end{aligned}$$

Given the expected value function, one can infer the optimal level of efforts e^*_{it} by the level at which they maximize $U(e_{it}, s_{it}) + \delta\mathrm{EV}(e_{it}, s_{it})$. Subsequently, the inferred efforts e^*_{it} enter the performance response function in Equation (2.1). Then, the likelihood of an agent's observations is computed by the distribution of Equation (2.4). Given the T-period observation of the performance $\mathbf{q_i}$ and state variables $\mathbf{s_i}$, the agent's likelihood becomes

$$L_i(\Omega_i; \mathbf{q_i}, \mathbf{s_i}) = \prod_{t=1}^{T} \prod_{q \in \{A,R,C,M\}} \varphi_{\xi,q} \left(\hat{q}_{it} - q_{it}\right),$$

where the vector ω_i is the set of structural parameters and $\hat{q}_{it}$ is the observed performance. $\varphi_{\xi,q}$ denotes the p.d.f. of a normal distribution with mean zero and variance $\sigma^2_{\xi,q}$ per task $q \in \{A, R, C, M\}$.

2.4 Results

This section presents the results in the following order. First, we show the parameter estimates of the model. Next, we present the counterfactual analyses and discuss their implications, with a focus on addressing the substantive questions of this study: How does sales incentive design affect organization's CRM performance (acquisition, retention, cross-selling, and monetization) in the short- and the long-terms?

2.4.1 Parameter Estimates

Table 2.7 reports the parameter estimates of the model. Regarding the utility function, the disutility estimates are 0.130, 1.505, 1.731, and 0.697, respectively for acquisition, retention, cross-sales, and monetization efforts. The results show that the per-unit disutility is small for acquisition, reflecting the agents' flexibility in exerting effort toward that task, and grows for retention and cross-sell.[12]

Regarding the acquisition response function, the beginning-of-period portfolio size has a negative effect on acquisition. Intuitively, an agent with a high market penetration would likely find it more challenging to tap new clients. The quotas for retention and cross-sell, which controls for market potential, both are positive and significant. Portfolio size has a positive effect on retention performance because a higher number of clients eventually grow into a bigger pool due for renewal.[13] Conversely, portfolio size has a mild negative effect on cross-sell performance, contrasting the evidence in Section

[12] Because acquisition is defined as the change in the number of clients, a renewed loan counts both as acquisition and retention outcomes. Hence, the disutility of retention, in the current empirical context, reflects agents' incremental cost to retain a customer.

[13] Retention performance is positively related to portfolio size because it is measured in counts. The portfolio-size implication may differ in other settings, e.g., if retention performance is measured relative to quota achievement.

Parameter	Estimate
Utility function	
Disutility of acquisition effort	**0.130**
Disutility of retention effort	**1.505**
Disutility of cross-selling effort	**1.731**
Disutility of monetization effort	**0.697**
Acquisition response	
Portfolio size	**−0.005**
S.D. of performance shock	**9.100**
Retention response	
Portfolio size	**0.001**
Retention quota	**0.061**
S.D. of performance shock	**0.505**
Cross-sell response	
Portfolio size	**−0.001**
Cross-sell quota	**0.141**
S.D. of performance shock	**0.615**
Monetization response	
Portfolio size	−0.000
S.D. of performance shock	**0.041**
Log-likelihood	−26,198
BIC	52,522

Notes. Significance at the 0.05 level appears in boldface. Standard errors are approximated by inverse of the Hessian of the log-likelihood and are omitted from the table for brevity.

Table 2.7: Parameter Estimates

2.2.3. This implies that, once agents' cross-sell effort is considered, the portfolio size negatively affects performance because those who need to manage a large client pool likely have less per-customer time and opportunity to engage in cross-selling tasks.

2.4.2 Counterfactual Analyses

This section discusses the results of several counterfactual simulations, which evaluate the changes in agents' behavior and outcome in response to alternative incentive policies. The counterfactuals suppose that the firm is undertaking its policy design at the beginning of 2016 (i.e., beginning of the data observation period). Agents' per-period quotas are set constant at their respective values in 2016. The basis for the changes is the February-May policy (hereafter, benchmark policy). For each new regime, we simulate 200 paths per individual using the parameter estimates of the model.

The simulation procedure is as follows: (1) Compute the value function using the estimated parameters. (2) Given agent's state, *infer* unobserved efforts across the tasks—the value at which they maximize the value function. (3) Using the inferred efforts and states, stochastically derive agent's performance outcomes.

Adjusting the Incentive Amount

A challenge in multi-component incentive design is to determine the optimal weight across different tasks. One might intuitively expect that increasing a task's incentive amount unequivocally promotes positive behavior and, thus, outcomes. However, this intuition does not always hold because the tasks are interdependent: under an additive (a multiplicative) structure, the underlying tasks serve as substitutes (complements). Further complications to predicting the outcomes arise due to varying level of disutility across tasks, as well as the dynamics surrounding CRM metrics.

Hence, the first counterfactual analysis examines the causal outcomes of adjusting the incentive amounts. Specifically, we change the incentive amount tied to each task, while keeping other components constant. For each policy, we simulate and aggregate agents' performance over a one-year horizon. Table 2.8 details the changes and the resulting performance outcomes across the four tasks, as well as the firm's compensation expense incurred due to the change, represented by the average annual incentive.

Counterfactual simulation	Acquisition (A)		Renewal (R)		Cross sales (C)		Delinquency (M)		Annual incentive	
	Outcome	Change	Outcome	Change	Outcome	Change	Outcome	Change	Outcome	Change
Benchmark	1.45	-	5.49	-	8.51	-	4.48	-	1,976	-
(a) Increase Acquisition Incentive by										
$ 5 / unit	2.94	⇑ 1.49	5.23	⇓0.25	8.41	⇓0.09	4.25	⇓0.23	2,394	⇑ 418
$ 10 / unit	3.51	⇑ 2.06	5.23	⇓0.26	8.35	⇓0.15	4.1	⇓0.38	2,692	⇑ 716
$ 15 / unit	3.73	⇑ 2.28	5.23	⇓0.26	8.33	⇓0.17	3.93	⇓0.54	2,968	⇑ 991
(b) Increase Retention Incentive by										
$ 5 / unit	1.25	⇓0.20	5.7	⇑ 0.22	8.52	0	4	⇓0.48	2,323	⇑ 347
$ 10 / unit	1.65	⇑ 0.20	5.72	⇑ 0.23	8.49	⇓0.01	3.92	⇓0.55	2,624	⇑ 648
$ 15 / unit	1.68	⇑ 0.23	6.31	⇑ 0.83	8.48	⇓0.02	3.9	⇓0.57	2,976	⇑ 1,000
(c) Increase Cross-sell Incentive by										
$ 5 / unit	0.98	⇓0.46	5.29	⇓0.20	10.7	⇑ 2.20	3.98	⇓0.49	2,413	⇑ 437
$ 10 / unit	0.86	⇓0.58	5.22	⇓0.27	12.63	⇑ 4.12	3.97	⇓0.51	2,778	⇑ 801
$ 15 / unit	0.9	⇓0.54	5.19	⇓0.29	13.63	⇑ 5.12	3.86	⇓0.61	3,168	⇑ 1,191
(d) Increase Delinquency Incentive/penalty by										
25%	3.52	⇑ 2.07	5.71	⇑ 0.23	8.37	⇓0.14	3.83	⇓0.64	3,069	⇑ 1,092
50%	5.13	⇑ 3.68	5.87	⇑ 0.39	8.31	⇓0.20	3.38	⇓1.10	4,297	⇑ 2,321
100%	6.92	⇑ 5.47	5.97	⇑ 0.48	9.22	⇑ 0.71	2.61	⇓1.87	7,018	⇑ 5,042

Notes. Benchmark plan denotes incentive structure #1. Acquisition, renewal, and cross-sales outcomes are in counts; Delinquency outcome is in percentages; Annual incentive amount is in U.S. dollars. The changes are relative to the benchmark. A positive (negative) outcome is marked in blue (red).

Table 2.8: Counterfactual Analysis: Incentive Amount

Panel (a) increases the acquisition incentive by \$5, \$10, and \$15 per unit[14] and keeps everything else constant. As anticipated, acquisition performance improves. However, the renewal and cross-sales performance falls, and the delinquency performance improves (i.e., the rate decreases). For acquisition, the incentive structure is additive in renewal and cross sales, and multiplicative in delinquency. Hence, the agents shift their effort from substitute tasks (renewal and cross sales) toward the focal task (acquisition) and its complementary task (delinquency). Hereafter, we use the term *structure effect* to collectively refer to the substitutability and complementarity arising from additive and multiplicative structures, respectively.

The results of increasing the retention and cross-sell incentives (see Panels (b) and (c)), in large, exhibit comparable structure effect—increasing the incentive amount on a task generally reduces performance of the substituting two tasks and improves the complementing delinquency rate.

Panel (d) shows the results of increasing the delinquency incentive by 25, 50, and 100% while keeping other incentives constant. Because delinquency is multiplicative on other three tasks, agents' extra motivation spills over to other tasks by the structure effect. The magnitude of spillover toward each task depends on the task's relative marginal costs (i.e., disutility) of exerting effort and possible pecuniary benefits in return. Hence, the acquisition outcome improves because of high per-unit return and low disutility of effort, followed by the retention outcome.

Throughout Table 2.8, however, we also observe a few inconsistent patterns that do not comply with the structure effect. For instance, increasing the retention incentive by \$10 or \$15 actually *improves* acquisition—which is a substitute task (see Panel (b)).

[14] The increase applies to positive incentive amounts under the benchmark policy (i.e., if the number of acquisitions, $A \geq 3$).

Also, increasing the delinquency incentive *decreases* cross-sales—which is a complementary task (see Panel (d)).

The inconsistencies arise because of the dynamics surrounding the CRM metrics, which we term the *CRM-dynamics*. As discussed in Section 2.3.3, an agent's acquisition effort today, by the evolution of portfolio-size state (i.e., the number of clients), persists and affects performance outcomes tomorrow. Such effect is positive for future retention and negative for future acquisition and cross sales (per the parameter estimates in Section 2.4.3).

To better understand the interplay between the two forces—the *structure effect* and the *CRM-dynamics*—Table 2.9 shows the ratio of *inferred* effort levels, comparing the alternative policies to the benchmark. From Panel (b), we find that the acquisition effort initially decreases as retention incentive increases. Hence, the structure effect is in order, and agents direct their extra efforts toward retention (and delinquency). However, as retention incentive grows further, acquisition effort grows because (i) exerting additional retention effort is costly and (ii) by exerting (the relatively less costly) acquisition effort, the prospects of future retention incentives increase. Consequently, the CRM-dynamics effect dominates, and acquisition performance improves over the benchmark.

Counterfactual	Acquisition (A)	Renewal (R)	Cross sales (C)	Delinquency (M)
(a) Increase Acquisition Incentive by				
$ 5 / unit	1.13	0.91	1.00	1.03
$ 10 / unit	1.19	0.90	0.99	1.05
$ 15 / unit	1.21	0.89	0.99	1.09
(b) Increase Retention Incentive by				
$ 5 / unit	0.98	1.08	1.00	1.12
$ 10 / unit	1.02	1.08	1.00	1.13
$ 15 / unit	1.02	1.19	1.00	1.13
(c) Increase Cross-sell Incentive by				
$ 5 / unit	0.96	0.95	1.65	1.12
$ 10 / unit	0.95	0.93	2.06	1.13
$ 15 / unit	0.95	0.92	2.22	1.15
(d) Increase Delinquency Incentive/penalty by				
25%	1.19	1.04	1.00	1.12
50%	1.33	1.08	1.02	1.20
100%	1.49	1.08	1.34	1.35

Notes. An increase (decrease) in effort compared to the benchmark is marked in blue (red).

Table 2.9: Counterfactual Analysis: Incentive Amount (Effort Comparison)

A similar logic holds when increasing the delinquency incentive/penalty. Panel (d) shows how the structure effect increases effort across all multiplicative tasks, including cross sales. Initially as the incentive grows, much of the effort shift is geared toward acquisition which, in turn, dampens future cross-sales outcomes. Hence, the CRM-dynamics kick in and, on average, the cross-sales outcome decreases. However, as the delinquency incentive grows further, the marginal gains from acquisition effort erode and, eventually, agents increase their cross-sales effort—i.e., the structure effect dominates—yielding positive performance.[15]

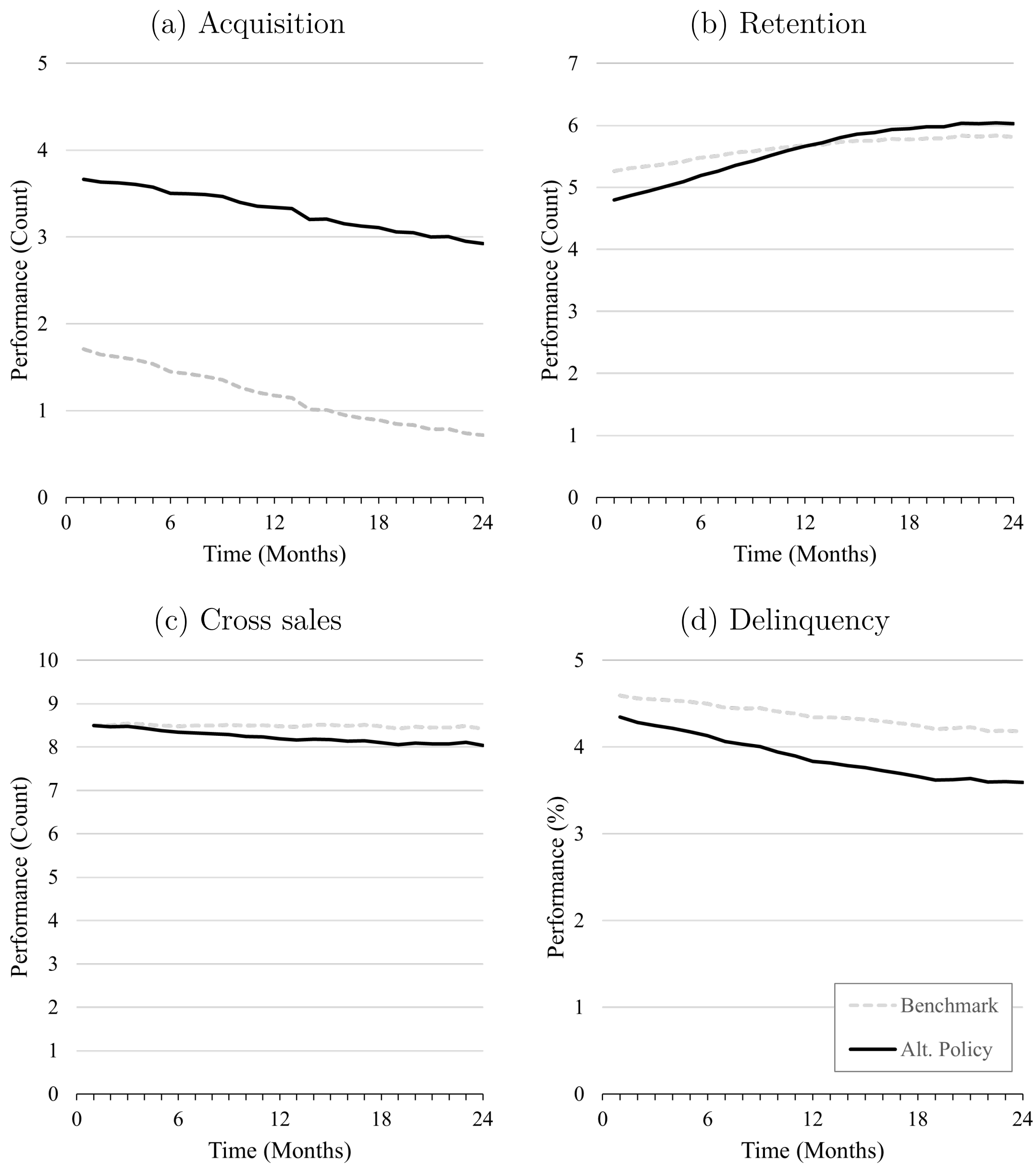
The Long-Term Effects of Incentive Design

The preceding section accounts only for aggregate performance outcomes. To assess the long-term implications of incentive design, this counterfactual simulation examines performance outcomes at the monthly level over a two-year horizon. The focal policy is increasing the acquisition incentive by \$10 (i.e., the second policy in Panel (a), Table 2.8). The case demonstrates the interdependence between acquisition and retention, as well as current and future acquisition.[16]

Figure 2.2 depicts long-term performance outcomes across the four tasks. The dark solid line shows the focal policy outcomes and gray dotted line shows the benchmark. Intuitively, acquisition performance increases in response to the additional reward (see Panel (a)). Initially following the change, a strong structure effect stimulates agents to align their effort toward acquisition and its complementary delinquency task, and away from substitute retention task. As a result, delinquency performance improves,

[15] A 100% increase in delinquency incentive is for an illustrative purpose. In practice, such a policy would involve excess costs to the firm as evidenced by the last line in Table 2.8.

[16] The results are robust to alternative acquisition incentive amounts and adjusting the retention incentive.



Notes. The solid line represents the alternative policy, which increases acquisition incentive by $10 per unit, and the dotted line represents the benchmark projections. The y-axis depicts performance in numbers (for acquisition, retention, and cross sales) and percentages (for delinquency), and the x-axis depicts time horizon.

Figure 2.2: Counterfactual Analysis: Long-Term Effects of Incentive Design

and retention performance drops during the early months (see Panels (b) and (d)).

As time passes, however, the initial gap between the focal policy and the benchmark evolves. It narrows for retention and widens for cross sales and delinquency tasks. Such developments are attributable to the CRM-dynamics effect. An increase in acquisition performance accumulates and grows the agents' portfolio size over time. On the one hand, this yields a positive effect on future retention, narrowing the gap as shown in Panel (b). Eventually, the focal policy *outperforms* the benchmark in terms of retention. On the other hand, the portfolio size growth adversely affects future cross sales and, as a result, the performance gap widens over time in Panel (c). Combining these effects, the focal policy's net impact on overall acquisition, retention, and cross-sales incentives (i.e., sum of additive components) grows over time. Hence, to take advantage of the additional incentives, agents' motivation to invest in delinquency task also grows and, thus, expands the performance gap (i.e., delinquency rate further improves) over time as shown in Panel (d).

2.4.3 Managerial Implications

Several important managerial implications for sales incentive design emanate from the counterfactual analyses. First, an organization's strategy to promote a certain CRM task by increasing its incentive amount may inadvertently generate a negative spillover toward other tasks. Specifically, salespeople reallocate their effort away from the un-promoted tasks, thereby harming the performance outcome of the other tasks. This is especially the case when the promoting task's incentive forms an additive structure with the rest.

Second, and relatedly, an organization that is short on budget but wanting to motivate a specific task can achieve its goal by *de-incentivizing a substitute task*. For instance, the focal firm, by reducing the retention incentive by \$5 per unit, can expect a 0.40-unit increase, on average, in acquisition performance (intuitively, the retention performance drops). The firm also saves \$167 spent on annual compensation expenses per salesperson. Therefore, the two seemingly countervailing objectives—promoting a task while saving costs—can be achieved by exploiting effort substitution arising from an additive incentive structure.

Third, organizations should be cautious about the repercussions of an ill-conceived multiplicative structure. In Section 2.4.2, we observed how a multiplicative structure induces spillover of agents' efforts (the structure effect). By increasing the incentive amount tied to a multiplicative component, an organization can expect improvements on all associated tasks. This implies, conversely, that decreasing the incentive amount may result in severe consequences because doing so dampens all other outcomes. More broadly, mis-setting an element in a multiplicative component (e.g., a poorly set quota, inadequate incentive amount) may induce negative spillover that demotivates multiple tasks. Hence, organizations should carefully design a multiplicative structure—and use field experiments or structural economic methods to evaluate any possible shortcomings.

Last, an organization should consider the long-term implications of their incentive design. Specifically, the dynamic effects brought about by the linkage across CRM metrics may yield outcomes that are not readily observed in a short period of time. Such dynamics, in conjunction with the incentive structure, determine salespeople's behavior and thus performance outcomes.

2.5 Conclusion

Designing a multi-component incentive plan is an elaborate process that requires understanding of the underlying tasks, the organization's desired outcomes, and salespeople's behaviors associated with those tasks. The weights and structures embedded in a multi-component incentive plan collectively determine the salespeople's degree of motivation and, thus, performance outcomes across multiple CRM responsibilities. If properly designed, the incentive plan effectively aligns salespeople's behaviors with organizational objectives, benefiting both parties alike.

To this end, this study develops and estimates a dynamic structural model of salespeople's behavior in response to a multi-component incentive plan. The model incorporates multiple tasks underlying CRM: acquisition, retention, cross-selling, and profitability. The study investigates the short- and long-term effects caused by an alternative incentive design, which varies the structure (i.e., additive vs. multiplicative) as well as the weight (incentive amount) attached to each component. The analysis shows ways in which multitasking salespeople's behaviors are interrelated and how salespeople shift their efforts across tasks in response to alternative incentive design. The results demonstrate: (i) how a stronger incentive on one task can lead to lower performance on other tasks; (ii) ways to promote a task while reducing overall compensation costs; (iii) the long-term CRM implications of incentive design; and (iv) the risks associated with inadequately designed multiplicative structure. This study contributes to the multitasking incentive literature by demonstrating how a multiplicative structure may serve as a double-edged sword and how attaching a multiplicative structure to rewards and an additive structure to penalties better motivate salespeople.

Substantively, this paper helps organizations (i) evaluate the effects, and possible tradeoffs, of choosing an additive vs. a multiplicative structure; (ii) understand how multiple incentive components interact with salespeople's behavior and how they reallocate effort in response to a new plan; and (iii) recognize the importance of a thoughtful incentive design, which affects both the short- and the long-term CRM outcomes. Collectively, this study provides guidance to organizations on the optimal design of their multi-component incentive plans.

In summary, this study offers a relevant, yet practical application to understand the implications of multi-component incentive design. We believe that the results will guide sales organizations better design an incentive policy that benefits the organization, its salespeople, and its customers in both the short- and the long-term.

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