The Comprehensive Effects of Sales Force Management: A Dynamic Structural Analysis of Selection, Compensation, and Training

Doug J. Chung, Byungyeon Kim, Byoung G. Park

Abstract. This study provides a comprehensive model of an agent’s behavior in response to multiple sales management instruments, including compensation, recruiting/termination, and training. The model takes into account many of the key elements that constitute a realistic sales force setting: allocation of effort, forward-looking behavior, present bias, training effectiveness, and employee selection and attrition. By understanding how these elements jointly affect agents’ behavior, the study provides guidance on the optimal design of sales management policies. A field validation, by comparing counterfactual and actual outcomes under a new policy, attests to the accuracy of the model. The results demonstrate a tradeoff between adjusting fixed and variable pay; how sales training serves as an alternative to compensation; a potential drawback of hiring high-performing, experienced salespeople; and how utilizing a leave package leads to sales force restructuring. In addition, the study offers a key methodological contribution by providing formal identification conditions for hyperbolic time preference. The key to identification is that under a multiperiod nonlinear incentive system, an agent’s proximity to a goal affects only future payoffs in nonpecuniary benefit periods, providing exclusion restrictions on the current payoff.

Keywords: sales force compensation • training • selection • recruiting • termination • hyperbolic discounting • present bias • dynamic structural models • exclusion restriction • identification

1. Introduction

Effective management of the sales force is vital to the success of sales-driven organizations. Approximately 15 million salespeople in the United States, representing about 10% of the entire U.S. labor force, serve as links between customers and firms (U.S. Department of Labor 2018). Investments in these salespeople are approximated to be 10% of sales revenues and can reach up to 40% in certain industries (Heide 1999). U.S. firms spend more than $800 billion on sales forces each year—nearly four times the estimated $208 billion they spend on media ($98 billion) and digital ($110 billion) advertising (Zoltners et al. 2013, MAGNA 2018). As these significant figures suggest, personal selling represents one of the most important elements of a firm’s marketing mix, highlighting the importance of managing and motivating salespeople to achieve the organization’s objectives.

Since the earliest days of personal selling, organizations have utilized three main sales (force) management instruments to better control and motivate the sales force: compensation, recruiting/retention (of high-ability employees), and training. Figure 1 illustrates the relation between these instruments and the organization’s sales performance. Performance is an outcome of salespeople’s behavior, and the sales management instruments are used for training and motivating proper behavior as well as for selecting the right types of people. Not only do the three key instruments differ in cost and effectiveness across different types of people, but they also are interconnected in their effectiveness at changing behavior and, thus, attaining the desired performance outcome. This study aims to jointly examine the effectiveness of multiple sales management instruments in the selection and performance of heterogeneous salespeople.

A key, if not the most important, instrument in sales management is compensation. Organizations frequently use compensation to motivate and control the behavior of salespeople. A sales force compensation system typically consists of fixed- and variable-pay
components, with each component playing a distinct role in managing sales force behavior. Fixed pay (base salary) compensates for risk and, thus, provides stability and security of income (Arrow 1971, Harris and Raviv 1978, Holmstrom 1979, Basu et al. 1985, Lal and Srinivasan 1993). Variable pay, by contrast, provides a direct link between the sales outcome and financial rewards, thereby inducing motivation to achieve superior performance. Examples of variable pay include commissions, given as a proportion of sales, and lump-sum bonuses, contingent on meeting a preset quota. According to Joseph and Kalwani (1998), 95% of U.S. firms utilize some form of variable pay to incentivize their salespeople, with the most frequently used forms being commissions and quota-based bonuses. Organizations also change the components of their incentive systems frequently. About 80% of U.S. firms revise their compensation programs every two years or less to better motivate salespeople and to tailor their behavior to the goal of the sales organization (Zoltners et al. 2012).

However, simply providing salespeople with an optimal menu of compensation is insufficient for an organization to achieve its desired sales outcome. To support the productivity of their sales force, organizations often rely on sales training, which serves to increase productivity, stimulate communication inside and outside the organization, reduce inter- and intradepartmental misunderstandings, enrich sales force morale, and decrease selling costs (Stanton and Buskirk 1987, Churchill et al. 1993, Dubinsky 1996). U.S. firms invest $15 billion annually in sales training programs and devote more than 33 hours per year to training each salesperson (Lorge and Smith 1998, Ingram et al. 2015). Thus, to effectively allocate resources across the sales management instruments, it is essential to properly assess and evaluate the outcomes of the organization’s sales training policy.

Whereas compensation and training serve to induce the right behavior, selection (recruitment/termination) affects the organization’s performance through changes in the sales force composition. Salespeople are known to exhibit a high rate of attrition: the estimated annual turnover rate of 27% is more than twice that of the average workforce in the United States (Richardson 1999). There are two types of employee selection: (1) firm-induced selection, which involves recruiting, retention, and termination, and (2) employee-induced selection, i.e., voluntary turnover. When properly managed, selection allows the organization to maintain a healthy sales force by retaining high-quality employees and terminating persistently low performers. However, selection—especially voluntary turnover—also involves substantial costs to the organization, including hiring and training expenditures, jeopardized customer relationships, and territory vacancies (Griffeth and Hom 2001, Boles et al. 2012). Hence, deriving a proper policy to control for sales force selection is vital to the success of a sales organization.

Despite the ubiquitous use of these sales management instruments, however, there is little insight into their joint effect on various behavioral outcomes. For instance, how should a firm design its compensation system to select the right salespeople—that is, to retain the high performers while discouraging the low performers—over time? Which is more effective in motivating salespeople to meet their goals, increasing monetary compensation or providing sales training opportunities? Can a recruiting/termination policy replace the role of compensation and, if so, at what cost?

Separately identifying each of these issues turns out to be problematic because various behavioral outcomes are often interrelated and occur simultaneously. Heterogeneous salespeople exhibit differences in productivity, time preference, and responsiveness to compensation components and training, which, in combination, determine an individual’s performance. The performance outcome results in compensation that influences employee attrition, which naturally leads to the selection of heterogeneous salespeople. This interrelated nature of behavioral outcomes necessitates an integrated model of sales force management.

There are two key challenges in modeling and identifying salespeople’s responses to various management instruments. First, data at the salesperson level on various management practices are difficult to obtain because many organizations treat human resources information as confidential. As a result, existing studies typically focus on a single sales management instrument such as compensation (Misra and Nair 2011, Chung et al. 2014). Second, a researcher observes neither the agent’s effort nor the agent’s time preference—that is, the degree to which immediate utility is favored over delayed utility. Rather, the researcher observes only the attrition decision and performance outcome over a specific period, both of which are likely correlated with the agent’s forward-looking allocation of effort and
outside opportunities. This requires a behavioral assumption about the link between a sales agent’s motives (e.g., how close the person is to achieving the quota at the end of the period) and the agent’s allocation of effort over time.

To overcome these challenges, we collaborate with a major multinational firm and formulate a comprehensive model of sales force behavior in response to various sales management practices. The model takes into account many of the key realistic elements of salespeople’s behavior, including allocation of effort, stay-or-leave decision, forward-looking behavior, present bias, and learning from training opportunities. Overall, we seek to gain insights into ways in which employee training, outside employment opportunities, and various components of compensation jointly affect the selection and performance of heterogeneous salespeople.

This study also makes an important methodological contribution to the economics and marketing literatures. The study provides a formal proof on the identification conditions of a hyperbolic discounting model—a more general structure than an exponential discounting model. An agent’s distance-to-quota (DTQ) under a nonlinear incentive system affects only the agent’s future payoffs in nonpecuniary benefit periods, providing exclusion restrictions on current payoffs to identify the agent’s time preference. However, identifying time preference in a hyperbolic discounting model becomes challenging when confronted with an agent’s continuous choice (e.g., effort). Existing studies are built largely on a discrete choice setting (Fang and Wang 2015, Abbring and Daljord 2020), and, thus, the identification results do not fully translate. This study offers a formal discussion of the associated limitations and provides proper regularity conditions for identifying a hyperbolic discounting model under continuous choice. Building on the theoretical identification results, the empirical application shows support for agents’ hyperbolic discounting time preferences. A hyperbolic discounting model can potentially explain agents’ seemingly irrational behaviors (such as extreme procrastination) that are difficult to explain with a standard discounting model but are commonly observed in the real world (Ainslie 1992, Kirby 1997, Frederick et al. 2002).

The estimation results reveal the existence of different types of salespeople who possess heterogeneous utility and time preferences. A series of counterfactual simulations shows ways in which salespeople’s performance and selection change with alternative compensation systems, recruiting/termination policies, and sales training opportunities. The results demonstrate a tradeoff relation between adjusting fixed and variable pay, a potential drawback of hiring only high-type salespeople, the short- and long-term outcomes of hiring rookies versus experienced salespeople, how a collective leave package can lead to selective departure of the sales force, and how sales training can serve as an alternative to providing additional compensation.

A field validation—that compares the actual sales records (following changes in sales management instruments) with the simulated counterfactual outcomes—demonstrates the accuracy and applicability of the model. Hence, this study’s framework and model can provide a practical application for organizations to foresee the effect of multiple sales management instruments on the behavior of their sales force.

The remainder of the study’s structure is as follows. Section 2 summarizes the related literature. Section 3 describes the institutional settings and provides model-free evidence that facilitates the empirical analyses. Section 4 presents the modeling framework of sales management and an agent’s dynamic optimization problem. Section 5 illustrates the identification of dynamic models under exponential and hyperbolic time preferences. Section 6 describes the estimation procedure. Section 7 discusses the estimation results, counterfactual simulations, and field validation. Section 8 concludes.

2. Related Literature
This study on multidimensional sales force management contributes to several streams of research. First and foremost, the study relates to the literature on sales force compensation. The theoretical studies on this topic find conflicting results regarding components that constitute an optimal compensation system. Early works of Basu et al. (1985) and Rao (1990), under the principal–agent framework of Hölstrom (1979), find that the optimal compensation system includes a salary and a nonlinear commission. More granularly, Hölstrom and Milgrom (1987) and Lal and Srinivasan (1993) show that in a multiperiod setting, only a linear contract can achieve the first-best outcome. In contrast, Oyer (2000) finds that a compensation system with a quota bonus and a linear overachievement commission is uniquely optimal when the participation constraints are unbinding. More recently, Schöttner (2016) derives conditions under which a commission plan dominates a bonus plan and vice versa, depending on the degree of the agent’s responsiveness to incentives.

The findings of empirical studies also have discrepancies. Oyer (1998), using aggregate sales data, finds that a quota-bonus system induces salespeople to manipulate the timing of sales, thereby negatively affecting performance. On the contrary, Steenburgh (2008), analyzing individual-level data, finds that a quota-bonus system induces additional effort that
provides net improvement in sales. A similar disparity is reported using dynamic models; for example, Misra and Nair (2011) and Chung et al. (2014) report contrasting findings regarding the effect of quota bonuses on sales performance.

This study’s contribution to this literature is twofold. First, it expands the scope of outcomes to discuss the dynamic selection of sales agents, providing a better understanding of how an organization’s compensation system facilitates the restructuring of its sales force. In addition, the study examines agents’ effectiveness gain through training along with their response to compensation. Both sales training and compensation serve as significant investments for organizations, and thus, this study allows the evaluation of the relative effectiveness of these sales management instruments. To the best of our knowledge, this study is the first to jointly examine the effect of multiple sales management instruments on sales force selection and performance.

Because selection, by definition, accompanies employee turnover, this study relates to the literature on sales force attrition. Existing studies have put emphasis on the negative aspects of salespeople’s departure. Richardson (1999) derives managerial measures for assessing the direct and indirect costs of turnover, and Darmon (2008) proposes a cost-benefit analysis of turnover for management efficiency. Using empirical analyses, Shi et al. (2017) finds that the negative effects vary, and Sunder et al. (2017) finds that attrition risk is the greatest for salespeople with moderate performance.

The aforementioned studies, however, are limited to evaluating the short-term effect of territory absence, potentially overlooking the selection process that takes place simultaneously. That is, if a firm can select the right salespeople, then despite the short-term loss, employee attrition may result in greater long-term profitability. Hence, this study contributes to the appropriate evaluation of attrition by investigating salespeople’s latent future potential. In addition, the structural approach of the study allows for various counterfactual policy simulations, whereas descriptive studies limit this applicability.

This study also relates to the literature on sales training effectiveness. Although various studies have emphasized the pivotal role of sales training on performance and have proposed conceptual frameworks (Walker et al. 1977, El-Ansary 1993, Honeycutt et al. 1995, Attia et al. 2005), only a handful of empirical studies have followed this footprint, likely because of difficulties in collecting data. In addition, early empirical studies, relying mainly on survey measures, have generated strikingly mixed findings, ranging from a 50% increase in performance (Martin and Collins 1991, Roman et al. 2002) to being largely uninfluential (Christiansen et al. 1996, Dubinsky 1996).

More recently, Kumar et al. (2014), by examining the effect of voluntary training opportunities on sales force lifetime value, shows that sales training indeed has a positive effect in both the short and long term. However, the paper evaluates only the correlation between salespeople’s self-selected training participation and outcomes and refrains from developing a causal inference. To identify the causal effect of training, Atefi et al. (2018) conducts a controlled field experiment that varies training policies across retail stores. The paper finds a positive relation between sales outcomes and the proportion of salespeople who receive training; however, it analyzes sales training only at the aggregate (store) level because of the institutional and experimental settings.

This study provides several insights to the literature by measuring the comprehensive effects of sales training. First, by analyzing the training records at the individual level, the study examines the differential effect of training opportunities across heterogeneous salespeople. Second, the dynamic model allows us to analyze the long-term effects of training, which affects not only the intertemporal performance outcomes but also the subsequent selection of the sales force. Third, the structural formulation of the model allows for cost-wise comparison between training and compensation policies, providing guidance to organizations on their resource allocation.

Finally, this study relates to the economics and psychology literatures on time preference and intertemporal decision making. People discount future payoffs, and to capture the behavioral response to present versus future outcomes, researchers have mainly used two models of time preference: exponential and hyperbolic discounting. The exponential discounting model assumes that people discount the future at a fixed rate per unit of time (Samuelson 1937, Dhami 2016), representing stationarity and time-consistent behavior. In contrast, the hyperbolic discounting model posits that people discount the immediate future from the present more than they do for the same time interval in the distant future (Ainslie 1975, Ainslie and Herrnstein 1981, Thaler 1981, Loewenstein and Prelec 1992, Laibson 1997, O’Donoghue and Rabin 1999), implying present bias and time-inconsistent behavior.

In terms of identifying time preference, Rust (1994) shows that the discount factor is generally not identified from naturally occurring data without further restrictions. Magnac and Thesmar (2002) generalizes this idea to provide conditions on exclusion restrictions—variables that do not affect an agent’s current payoff but only the agent’s future payoff—that allow the
identification of the discount factor. Empirical studies in economics and marketing have applied exclusion restrictions to identify time preference (discount factor) across various contexts, including durable goods (Chevalier and Goolsbee 2009, Ishihara and Ching 2019), cellular phone usage (Yao et al. 2012), two-sided markets (Lee 2013), sales force compensation (Chung et al. 2014), and consumer stockpiling (Ching et al. 2014, Akca and Otter 2015, Ching and Osborne 2020).

In a debate in the literature, Fang and Wang (2015) and Abbring and Daljord (2020) discuss identification of time preference in dynamic discrete choice models. Fang and Wang (2015), by extending the exclusion restriction arguments in Magnac and Thesmar (2002), considers conditions to identify various discounting behaviors, including exponential, hyperbolic, and naive time preferences. Abbring and Daljord (2020) considers exclusion restrictions on model primitives and suggest that the arguments presented in Fang and Wang (2015), under weaker conditions, may not allow for point identification of the discount factor.

Different from these studies (in which choice is observed), this study’s identification allows the agent’s action (e.g., effort) to be unobserved and only indirectly inferred from the observable output (e.g., performance). Regarding identification of models involving unobserved choice variables, Hu and Xin (2019) provides a general framework under which the conditional choice probability and the law of motion for state variables are separately identified. The paper’s identification leverages exclusion restrictions that affect only the conditional choice probability but not the state transition probability. Similar to Hu and Xin (2019), this study identifies the agent’s unobserved effort using variation in output (sales performance) in response to the agent’s state (DTQ). The agent’s DTQ, under a nonlinear incentive system provides exclusion restrictions by affecting only future payoff (through the evolution of state variables) but not current payoff in non-pecuniary benefit periods.

This study contributes to this stream of literature by expanding the scope of identification to a quasi-hyperbolic discounting model that incorporates continuous choice of the agent’s actions. The study shows the limitations in applying the results of identification in a discrete choice setting (Magnac and Thesmar 2002, Fang and Wang 2015, Abbring and Daljord 2020) to a hyperbolic discounting structure that accommodates continuous choice and provides regularity conditions for identification. Building on the identification arguments, the empirical application presents support for agents’ hyperbolic discounting time preferences that exhibit heterogeneity in both the present-bias and long-term discount factors.

### 3. Institutional Details and Descriptive Analysis

This section presents the focal institution’s sales environment, its compensation plan, and model-free evidence on forward-looking behavior and allocation of effort, which justify the dynamic structural formulation of the model.

#### 3.1. Sales Environment

The firm under study is a multinational generic pharmaceutical company offering a portfolio of branded prescription products through its own direct sales force. The data come from the firm’s sales operations in Turkey. Some notable aspects of the Turkish pharmaceutical market are worth mentioning. First, the government heavily regulates prices. Second, the nation’s universal healthcare system induces a high level of competition among the generics companies. Third, the country’s regulations prohibit direct-to-consumer advertising as is the case in most other markets. As such, personal selling plays an important—and the only—role in the firm’s go-to-market strategy. Thus, recruiting and maintaining a sustainable pool of salespeople and training and motivating them properly are critical factors for success.

The data consist of salespeople’s performance, turnover, and hours of training during a three-year period (2015–2017). Table 1 shows the number of employees who joined and departed and the corresponding turnover rate for each year. The firm’s average voluntary turnover rate was 14.60% over the three years. We focus our attention on individuals who have remained in the firm (stay) and those who have voluntarily separated (quit). To minimize the effect of the initial learning curve, we discard individuals with fewer than or equal to three months since hire (i.e., who joined on or after October 2017). The data-cleaning process leaves us with 554 salespeople. Table 2 shows the corresponding descriptive statistics. Employees who decided to stay with the firm tend to perform better, receive higher variable pay, and have longer tenure.

The firm offers three types of sales training programs: primary training session, year-end sales

| Table 1. Sales Force Turnover |

<table>
<thead>
<tr>
<th>Year</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beginning</td>
<td>303</td>
<td>330</td>
<td>367</td>
</tr>
<tr>
<td>Joined</td>
<td>58</td>
<td>102</td>
<td>91</td>
</tr>
<tr>
<td>Departed</td>
<td>31</td>
<td>65</td>
<td>58</td>
</tr>
<tr>
<td>Year end</td>
<td>330</td>
<td>367</td>
<td>400</td>
</tr>
<tr>
<td>Turnover rate, %</td>
<td>9.79</td>
<td>18.65</td>
<td>15.12</td>
</tr>
</tbody>
</table>

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session, and new sales-employee orientation. The 12-hour primary training session took place twice during the data observation period: one in January 2015, targeted at the salespeople from the primary care division (representing half the entire sales force), and the other in April 2016, targeted toward senior salespeople across all divisions. The three-hour year-end sales session, which took place in December 2016, was mandatory for all salespeople. In 2017, the firm introduced a new sales-employee orientation program (designed for salespeople with less than one year of tenure) that ran for three hours. The estimated hourly cost of sales training per salesperson was $37 in 2016.

The firm operates its sales activity by route call sales: each salesperson has a preplanned series of meetings with either physicians or pharmacists in the salesperson’s exclusive territory. On average, a salesperson makes 20 calls per day. During each meeting, the salesperson exerts effort to promote the firm’s range of products.

3.2. The Firm’s Compensation Plan

The firm’s compensation plan consists of three components: base salary, quota-based bonus, and overachievement commission. Figure 2 illustrates an overview of the plan, and Table 3 describes the specifics of the quota-bonus-payment schedule. The salespeople, on average, receive a fixed monthly salary of $1,500. At the end of the first three quarters, a salesperson receives a $1,700 bonus if he or she has attained the respective quotas. At the end of the year, the firm gives a $3,400 bonus if the salesperson has met the annual quota. In addition, salespeople receive an overachievement commission of approximately $170 (2% of the combined bonuses of $8,500) per any excess percentage points above the annual quota. The firm caps the overachievement commission at $8,500, attained when the salesperson’s performance (sales/ quota realization) reaches 150%.

In setting and updating the agents’ quotas, the firm uses a well-established consulting company (that gathers all the pharmaceutical sales data in the country,

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>All</th>
<th>Stay</th>
<th>Quit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of salespeople</td>
<td>554</td>
<td>400</td>
<td>154</td>
</tr>
<tr>
<td>Monthly base salary, USD</td>
<td>Mean</td>
<td>1,513.58</td>
<td>1,549.13</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>268.01</td>
<td>271.49</td>
</tr>
<tr>
<td>Annual variable pay, USD</td>
<td>Mean</td>
<td>5,611.07</td>
<td>6,242.38</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>3,796.17</td>
<td>4,347.77</td>
</tr>
<tr>
<td>Tenure, years</td>
<td>Mean</td>
<td>4.08</td>
<td>4.63</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>4.56</td>
<td>4.75</td>
</tr>
<tr>
<td>Sales training, hours per year</td>
<td>Mean</td>
<td>3.46</td>
<td>3.79</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>0.66</td>
<td>0.63</td>
</tr>
<tr>
<td>Higher education, %</td>
<td>Mean</td>
<td>93.68</td>
<td>93.50</td>
</tr>
<tr>
<td>Annual performance, %</td>
<td>Mean</td>
<td>95.12</td>
<td>97.50</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>15.35</td>
<td>13.01</td>
</tr>
<tr>
<td>Meet 100% quota, %</td>
<td>Q1</td>
<td>Mean</td>
<td>42.36</td>
</tr>
<tr>
<td></td>
<td>Q2</td>
<td>Mean</td>
<td>41.31</td>
</tr>
<tr>
<td></td>
<td>Q3</td>
<td>Mean</td>
<td>39.16</td>
</tr>
<tr>
<td></td>
<td>Annual Mean</td>
<td>42.04</td>
<td>46.88</td>
</tr>
</tbody>
</table>

Note. The numbers are approximate for confidentiality.

Figure 2. Firm’s Compensation Plan

Table 2. Descriptive Statistics

Note. The numbers are approximate for confidentiality.

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including those of the firm’s competitors) to incorporate market-level information, such as current share, growth potential, and territorial and seasonal fluctuations in demand. By adjusting quotas based on objective measures (rather than on past sales performance), the firm mitigates possible ratcheting concerns.

Some features of the firm’s quota-based bonus system are noteworthy. First, quotas are set to be cumulative from the beginning of the year. Second, the firm defers the unearned bonus amount in each quarter to the subsequent quarter. That is, if a salesperson misses the quota in a given quarter, the respective bonus amount is added to the total amount attainable in the next quarter. For example, if a salesperson meets both quarter 1 (Q1) and Q2 quotas, the salesperson would receive $1,700 in both March and June. However, if a salesperson misses only the Q2 quota and not the Q1 quota, the salesperson would receive $3,400 only in June.

This payout structure creates unique dynamics in the forward-looking behavior of the salespeople. On the one hand, it motivates them to keep up the pace from the beginning of the year. If a salesperson performs adequately and achieves a bonus in a given period, the salesperson’s motivation remains intact because of the attainable quarterly bonus in the next period. If the salesperson does not meet the quota in a given quarter, the motivation to exert effort becomes greater in the subsequent periods because incentives increase as a result of the deferred bonus amounts from the previous quarters.

On the other hand, the cumulative nature of the performance evaluation also raises potential concerns in which poor performers lose motivation and give up. Because the sales/quota realization accumulates from the beginning of the year, the effect of several negative sales shocks can have a lasting effect throughout the year. This could demotivate the salespeople with poor performance during the early part of the year, whereas they would have received a fresh start under an independent quarterly quota system.

### 3.3. Model-Free Evidence: Forward-Looking Behavior

If salespeople’s proximity to bonuses (i.e., DTQ) affects their performance in nonbonus periods, this suggests forward-looking behavior (Chung et al. 2014). Specifically, the state of DTQ would affect the performance of salespeople who have a reasonable chance of achieving the bonus. Hence, to show evidence of forward-looking behavior, we divide salespeople by their cumulative quota achieved (%QA): when %QA > 0.8, salespeople have a reasonable probability of attaining the bonus at the end of each quarter, but when %QA < 0.8, the chance is slim. In addition, the probability likely decreases as time passes and performance accumulates. Table 4 reports the results of a regression analysis, with each column having monthly performance as the dependent variable and %QA by the previous month as the explanatory variable, separately for each group of salespeople who are %QA > 0.8 and %QA < 0.8. Hereafter, the term performance denotes sales normalized by the agent’s corresponding monthly quota, which are used to construct the cumulative interim and annual quotas. As indicated in Section 3.2, quotas are set by a well-established consulting firm, taking into account territorial and seasonal fluctuations in demand.

### Table 3. Variable Compensation Payout Ratio (2017)

<table>
<thead>
<tr>
<th>Performance (sales/quota)</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0% – 89.99%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>90% – 90.99%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>35%</td>
</tr>
<tr>
<td>91% – 91.99%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>41%</td>
</tr>
<tr>
<td>92% – 92.99%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>47%</td>
</tr>
<tr>
<td>93% – 93.99%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>53%</td>
</tr>
<tr>
<td>94% – 94.99%</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>59%</td>
</tr>
<tr>
<td>95% – 95.99%</td>
<td>—</td>
<td>65%</td>
<td>65%</td>
<td>65%</td>
</tr>
<tr>
<td>96% – 96.99%</td>
<td>—</td>
<td>72%</td>
<td>72%</td>
<td>72%</td>
</tr>
<tr>
<td>97% – 97.99%</td>
<td>—</td>
<td>79%</td>
<td>79%</td>
<td>79%</td>
</tr>
<tr>
<td>98% – 98.99%</td>
<td>—</td>
<td>86%</td>
<td>86%</td>
<td>86%</td>
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<tr>
<td>99% – 99.99%</td>
<td>—</td>
<td>93%</td>
<td>93%</td>
<td>93%</td>
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<tr>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
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<tr>
<td>Greater than 100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>101%-200%</td>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Bonus amount</td>
<td>$1,700</td>
<td>$1,700</td>
<td>$1,700</td>
<td>$3,400</td>
</tr>
</tbody>
</table>

Note. The quarterly variable compensation 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 4. Relation Between Sales Performance and Distance-to-Quota

<table>
<thead>
<tr>
<th>State</th>
<th>Variable</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>April</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>Aug</th>
<th>Sept</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>%QA &lt; 0.8</td>
<td>Intercept</td>
<td>0.71</td>
<td>0.83</td>
<td>0.63</td>
<td>0.49</td>
<td>0.47</td>
<td>0.84</td>
<td>0.67</td>
<td>0.49</td>
<td>0.50</td>
<td>0.43</td>
<td>0.38</td>
<td></td>
</tr>
<tr>
<td></td>
<td>%QA</td>
<td>(0.04)</td>
<td>(0.11)</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.10)</td>
<td>(0.11)</td>
<td>(0.13)</td>
<td>(0.15)</td>
<td>(0.15)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>%QA &gt; 0.8</td>
<td>Intercept</td>
<td>0.70</td>
<td>0.74</td>
<td>0.55</td>
<td>0.39</td>
<td>0.49</td>
<td>0.26</td>
<td>0.12</td>
<td>0.60</td>
<td>0.21</td>
<td>−0.27</td>
<td>−0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>%QA</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.09)</td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.11)</td>
<td></td>
</tr>
</tbody>
</table>

Notes. The table shows the results of regression analyses where for each column monthly performance is the dependent variable and the cumulative quota achieved (%QA) by the previous month (respectively for each group of salespeople who are %QA > 0.8 and %QA < 0.8) is the independent variable. Standard errors are reported in parentheses. Significance (at the 0.05 level) appears in bold.

Consistent with forward-looking behavior, the (state) variable %QA is significant throughout the year for salespeople with %QA > 0.8. However, for those with %QA < 0.8, %QA is significant only during earlier periods of the year. This is the case because despite some bad outcomes during the earlier months, there still exists some probability of meeting the quota by achieving high performance for the remainder of the year. However, the chance of achieving the quota decreases as months with low performance accumulate, and by midyear, the low-performing salespeople (%QA < 0.8) start to give up.

For a graphic illustration of forward-looking behavior, Figure 3 displays the scatterplot and the best-fitting nonparametric smoothed polynomial (and its 95% confidence interval) of the salespeople’s performance in bonus-paying months on the %QA by the previous month. Three observations are noticeable. First, from March through September, a considerable number of salespeople with low %QA achieve monthly performance greater than 100%. However, in December, very few in the lower group exhibit excess performance. Consistent with the results in Table 4, salespeople far from the quota likely give up in December because they cannot achieve the annual quota in just a month. Second, a salesperson’s effort increases as he or she is on track to meet quota but flattens once the quota is met (%QA > 1). The proximity to bonuses (DTQ) motivates the salesperson, but once the salesperson surpasses quota (%QA > 1), the motivation is less present. Finally, a salesperson’s marginal effort with regard to his or her state (%QA by the previous month) increases with time in a calendar year. That is, the slope of the fitted line is steeper in December than in March. There are two likely reasons: (1) the presence of the overachievement commission in December motivates salespeople to exert greater effort, and (2) the large year-end bonus (including the overachievement commission) is less discounted because of temporal proximity and, thus, motivates salespeople more toward the end of the year.

4. Model

This section presents a comprehensive model of a sales agent’s behavior based on the sales management framework illustrated in Figure 1. The discussion proceeds in three parts: (1) the agent’s per-period utility and performance response functions, (2) dynamic allocation of effort and stay-or-leave decisions, and (3) time preference.

An agent derives utility from compensation and disutility from effort and faces intertemporal employment (stay-or-leave) decisions. Compensation is nonlinear and dependent on the history of performance (e.g., quarterly sales outcomes). Hence, the agent exhibits forward-looking behavior and dynamically allocates effort.

4.1. Per-Period Utility and Performance Response

Agent \(i\) in period \(t\) derives per-period utility based on his or her choice of actions—whether to stay with the firm \((d_{it} = 1)\) and (if so) how much effort to exert \((e_{it})\) such that

\[
\tilde{U}(W_{it}, d_{it}, e_{it}, \psi_{it}) = \begin{cases} 
    M(W_{it}) - C(e_{it}) + \psi_{it}, & \text{if } d_{it} = 1, \\
    \rho_i + \psi_{it}, & \text{otherwise}.
\end{cases}
\]  

If the agent decides to stay with the firm \((d_{it} = 1)\), the agent receives positive pecuniary utility \(M(W_{it})\) as a function of compensation \(W_{it}\). The amount of compensation \(W_{it} = W(q_{it}, s_{it}; \psi_{it})\) is determined by the agent’s performance \(q_{it}\) and state \(s_{it}\) given the firm’s compensation scheme \(\psi_{it}\). Concurrently, the agent incurs disutility \(C(e_{it})\) from exerting effort \(e_{it}\), which affects the performance outcomes in the contemporaneous period. If the agent decides to quit \((d_{it} = 0)\), he or she receives reservation value \(\rho_i\) in perpetuity. The reservation value represents the agent’s outside option. The decision to leave the firm is an absorbing state...
(i.e., permanent), and, thus, the agent cannot return to the firm once the action is taken. In addition to the deterministic elements, the period utility includes a structural error term $\varepsilon_{dit}$, which represents the state unobserved by the researcher but observed by the agent in his or her stay-or-leave decision $d_{it}$. The structural error follows a type I extreme value distribution with a location parameter of zero and a scale parameter of $\sigma_{e}$. It is assumed to be independently and identically distributed across choices and agents over time.

The agent’s per-period performance $q_{it}$ is a function of his or her individual effect $\alpha_{i}$, effort $e_{it}$, and an idiosyncratic performance shock $\xi_{it}$ such that

$$q_{it} = \exp(\alpha_{i} + e_{it} + \xi_{it})$$

or, in logarithmic terms,

$$\ln(q_{it}) = \alpha_{i} + e_{it} + \xi_{it}$$

The log-linear specification allows the agent’s sales performance to be always positive, consistent with the empirical setting. The individual effect (heterogeneity) $\alpha_{i}$ represents the agent’s baseline ability (i.e., performance attained without any effort). The performance shifters $x_{it}$ affect individual heterogeneity such that $\alpha_{i} = \alpha_{0} + \alpha_{1}x_{it}$, where $x_{it}$ includes the agent’s tenure, training, tenure-training interaction, and level of higher education. An agent’s cumulative hours of sales training forms the training variable to capture the long-run persistence effect. By this structure, the training hours accumulate to form the agent’s stock of expertise, which carries over to the subsequent periods and affects his or her performance over time. The distribution

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**Figure 3. Performance and Cumulative Quota Achieved (%QA)**

(a) March  
(b) June  
(c) September  
(d) December

*Note.* The $y$-axis depicts performance (sales/quota) in the bonus-paying months, and the $x$-axis shows the corresponding agent’s cumulative quota achieved (%QA) by the previous month.
of the performance shock $\xi_t$ (common knowledge to the agent) follows $N(0, \sigma^2_t)$ and is independent of the agent’s state $(s_{it}, a_t, \epsilon_{it})$ and effort $e_{it}$ for any $s \leq t$.

By the performance response function in Equation (2), the agent’s unobserved effort $e_{it}$ is stochastically linked to his or her observed performance $q_{it}$ in a given period. The performance outcome $q_{it}$, in turn, has both (1) a direct effect on contemporaneous compensation $W_{it} = W(q_{it}, s_{it}; \psi_{it})$ in bonus/commission periods and (2) an indirect effect on future compensation through evolution of the state variables $s_{it+1} = f(q_{it}, s_{it}; \psi_{it})$, where $f(\cdot)$ is the state transition function.

Equation (1) represents the ex post utility of the agent because the performance shock $\xi_{it}$ in Equation (2), which affects $W_{it}$ through $q_{it}$ in a given period, has yet to be realized when making the stay-or-leave and effort decisions. To form the basis of decision making, the agent takes expectation over his or her compensation $W_{it} = W(q_{it}, s_{it}; \psi_{it})$ given effort $e_{it}$ (which determines performance outcome $q_{it}$ under current state $s_{it}$). In this manner, the ex ante utility function of the agent is

$$U(d_{it}, e_{it}, s_{it}, \xi_{it}) = \left\{ \begin{array}{lll} E[M(W_{it})|e_{it}, s_{it}] - C(e_{it}) + \epsilon_{it}, & \text{if } d_{it} = 1, \\ \rho_i + \epsilon_{0it}, & \text{otherwise}, \end{array} \right.$$  

where the functions $M$ and $C$ take on a parametric functional form. The pecuniary utility $M$ of wealth $W_{it}$ takes the form of a mean-variance utility such that

$$E[M(W_{it})|e_{it}, s_{it}] = E[W_{it}|e_{it}, s_{it}] - \gamma_i \text{var}[W_{it}|e_{it}, s_{it}],$$

where $\gamma_i > 0$ represents the agent’s risk preference. The disutility $C$ is specified to be convex in effort $e_{it}$ such that

$$C(e_{it}) = \theta_i e_{it}^2,$$

where $\theta_i > 0$ denotes the agent’s ease and flexibility in exerting effort. An implicit benefit of the mean-variance utility specification is that it provides, by construction, scale and location normalization of utility. This allows us to estimate rather than to normalize the agent’s reservation value $\rho_i$ and the scale parameter $\sigma_e$ of the structural errors (see Section 5.4 for a detailed discussion of identification).

Given these specifications, the ex ante utility (hereafter simply referred to as utility) function can be represented as

$$U(d_{it}, e_{it}, s_{it}, \xi_{it}) = \left\{ \begin{array}{lll} E[W_{it}|e_{it}, s_{it}] - \gamma_i \text{var}[W_{it}|e_{it}, s_{it}] - \theta_i e_{it}^2 + \epsilon_{it}, & \text{if } d_{it} = 1, \\ \rho_i + \epsilon_{0it}, & \text{otherwise}. \end{array} \right.$$

The reservation value shifters $z_t$ affect the agent’s reservation value $p_t$ such that $p_t = p_{0it} + p_z z_{it}$, where $p_{0it}$ represents agent $i$’s baseline reservation value. Reservation value shifters $z_{it}$ include tenure and the level of higher education.

### 4.2. Compensation and State Variables

This study focuses on a class of nonlinear compensation systems, the payout of which depends on aggregate performance over a specific time horizon. These compensation systems typically include variable pay components, such as quarterly/annual bonuses or end-of-year commissions, which are commonly administered in practice (Joseph and Kalwani 1998). By providing a reward at the end of a quota-evaluation cycle consisting of multiple periods, the compensation system stimulates the sales agent’s forward-looking behavior because his or her effort exerted today affects his or her future payoff. The accumulation of effort is captured by a subset of the state variables in $s_{it}$, whose subsequent-period values $s_{it+1}$ evolve as a function of current-period performance $q_{it}$ and state $s_{it}$.

The firm’s incentive scheme ($\psi_{it}$) includes the following elements: (1) individual-specific monthly base salary $w_{it}$, (2) maximum attainable quarterly bonus amount $Q_i$ (including the deferred amount from previous periods), common across all agents but varying across years, (3) quarterly-bonus-payout rate $R_t$, and (4) end-of-year overachievement commission rate $O_i$.

Formally, the elements $Q_i$, $R_t$, and $O_i$ are as follows:

$$Q_i = \left\{ \begin{array}{cl} 1,700, & \text{if } s_{it} = 3, \\ 3,400, & \text{if } s_{it} = 6, \\ 5,100, & \text{if } s_{it} = 9, \\ 8,500, & \text{if } s_{it} = 12, \\ 0, & \text{otherwise}, \end{array} \right.$$

$$R_t = \left\{ \begin{array}{cl} 0.35, & \text{if } 0.90 \leq s_{2,t+1} < 0.91 \text{ and } s_{it} = 12, \\ 0.41, & \text{if } 0.91 \leq s_{2,t+1} < 0.92 \text{ and } s_{it} = 12, \\ 0.47, & \text{if } 0.92 \leq s_{2,t+1} < 0.93 \text{ and } s_{it} = 12, \\ 0.53, & \text{if } 0.93 \leq s_{2,t+1} < 0.94 \text{ and } s_{it} = 12, \\ 0.59, & \text{if } 0.94 \leq s_{2,t+1} < 0.95 \text{ and } s_{it} = 12, \\ 0.65, & \text{if } 0.95 \leq s_{2,t+1} < 0.96 \text{ and } s_{it} \in (6,9,12), \\ 0.72, & \text{if } 0.96 \leq s_{2,t+1} < 0.97 \text{ and } s_{it} \in (6,9,12), \\ 0.79, & \text{if } 0.97 \leq s_{2,t+1} < 0.98 \text{ and } s_{it} \in (6,9,12), \\ 0.86, & \text{if } 0.98 \leq s_{2,t+1} < 0.99 \text{ and } s_{it} \in (6,9,12), \\ 0.93, & \text{if } 0.99 \leq s_{2,t+1} < 1.00 \text{ and } s_{it} \in (6,9,12), \\ 1.00, & \text{if } 1.00 \leq s_{2,t+1} \text{ and } s_{it} \in (3,6,9,12), \\ 0, & \text{otherwise}, \end{array} \right.$$

$$O_i = \left\{ \begin{array}{cl} 1.00, & \text{if } 1.00 \leq s_{2,t+1} < 1.01 \text{ and } s_{it} = 12, \\ 1.02, & \text{if } 1.01 \leq s_{2,t+1} < 1.02 \text{ and } s_{it} = 12, \\ \vdots, & \text{otherwise}, \end{array} \right.$$

$$1.98, & \text{if } 1.49 \leq s_{2,t+1} < 1.50 \text{ and } s_{it} = 12, \\ 2.00, & \text{if } 1.50 \leq s_{2,t+1} \text{ and } s_{it} = 12, \\ 0, & \text{otherwise}, \right.$$
where the state variable $s_{i1t}$ denotes the month type ($1, 2, ..., 12$), and $s_{i2t}$ denotes the percentage of cumulative quota achieved (%QA) by the end of the previous month. The compensation elements are collected to represent the firm’s incentive scheme by the vector $\psi_{it} = \{w_{it}, Q_i, R_i, O_i\}$. Given the incentive scheme $\psi_{it}$, an agent receives compensation $W_{it} = W(q_{it}, s_{i1t}; \psi_{it})$ based on performance $q_{it}$ and state $s_{i1t}$. Compensation $W_{it}$ comprises three components: (1) monthly base salary $w_{it}$, (2) quarterly (and annual) bonus $QB_{it}$, and (3) end-of-year overachievement commission $OC_{it}$ in the following form:

$$W_{it} = w_{it} + QB_{it} + OC_{it},$$

whose components $QB_{it}$ and $OC_{it}$ are expressed as follows:

$$QB_{it} = \max \left(Q_t \cdot R_t \left(\frac{(s_{i1t} - 1) \cdot s_{i2t} + q_{it}}{s_{i1t}}\right) - s_{i3t}, 0\right),$$

$$OC_{it} = Q_t \cdot O_t \left(\frac{(s_{i1t} - 1) \cdot s_{i2t} + q_{it}}{s_{i1t}}\right),$$

where $s_{i3t}$ represents the amount of bonus accrued (%BA) in previous quarters (limiting the deferral of the quarterly-bonus amount if the agent previously received the bonus). Note that in nonbonus periods, $QB_{it} = 0$, and, thus, $W_{it}$ depends solely on $w_{it}$; note also that $OC_{it}$ is paid only in December.

The state variables directly linked to compensation include (1) the month type $s_{i1t}$, (2) the percentage of cumulative quota achieved (%QA) $s_{i2t}$, and (3) the amount of annual bonus accrued (%BA) $s_{i3t}$.

The state variables evolve as follows:

1. Month type

   $$s_{i1t} = \begin{cases} 1, & \text{if } t \text{ is the start of the year}, \\ s_{i1(t-1)} + 1, & \text{otherwise}. \end{cases}$$

2. Percentage of cumulative quota achieved (%QA)

   $$s_{i2t} = \begin{cases} 0, & \text{if } t \text{ is the start of the year}, \\ s_{i1(t-2)} \cdot s_{i2(t-1)} + q_{i(t-1)}, & \text{otherwise}. \end{cases}$$

3. Percentage of annual bonus accrued (%BA)

   $$s_{i3t} = \max \left(Q_{(t-1)} \cdot R_{(t-1)} \left(\frac{(s_{i1(t-2)} \cdot s_{i2(t-1)} + q_{i(t-1)})}{s_{i1(t-1)}}\right), s_{i3(t-1)}\right),$$

   otherwise.

Whereas the month type evolves in a self-contained manner, the latter two state variables evolve (stochastically) based on the agent’s effort. The percentage of cumulative quota achieved (%QA) evolves every month based on the performance in previous periods. The percentage of annual bonus accrued (%BA) evolves step-wise every quarter based on receiving the quarterly bonus. The state variables that directly affect compensation are represented by the vector $s_{it} = \{s_{i1t}, s_{i2t}, s_{i3t}\}$.

### 4.3. Dynamic Allocation of Actions

The per-period utility function in Equation (3), when linked with the aforementioned course of actions, outcomes, and state transitions, naturally leads to a dynamic formulation of the model. An agent chooses actions that solve the dynamic optimization problem, maximizing the sum of current and future payoffs over discrete periods ($t = 1, 2, ..., \infty$). The value function is defined as the agent’s discounted present value of the expected utility stream (given states $s_{it}$ and $e_{it}$) such that

$$v(s_{it}, e_{it}) = \mathbb{E} \left[ \sum_{t=1}^{\infty} \phi(t) \left( \max_{d_{it}, e_{it}} U(d_{it}, e_{it}, s_{it}, s_{dit}) \right) \mid s_{it}, e_{it} \right]$$

$$= \max_{d_{it}, e_{it}} \mathbb{E} \left[ U(d_{it}, e_{it}, s_{it}, s_{dit}) \right] + \mathbb{E} \left[ \sum_{t=1}^{\infty} \phi(t) \left( \max_{d_{it}, e_{it}} U(d_{it}, e_{it}, s_{it}, s_{dit}) \right) d_{it}, e_{it}, s_{it}, e_{dit} \right].$$

where $\phi(t)$ denotes the discount function for utility from future $j$ periods forward ($j = 0, 1, 2, 3, ...$), and $\phi(0) = 1$. Hence, the agent’s value is represented by the expected utility flow on making an infinite sequence of optimal decisions ($d_{it}, e_{it}; \tau = t, t+1, ...$) governed by the discount function $\phi(\cdot)$. The expectation is taken with regard to both the idiosyncratic performance shock $\xi_{it}$ and the structural error $e_{it}$ for each period $\tau \geq t + 1$.

The choice-specific value with respect to action pair $(d_{it}, e_{it})$, which represents the discounted present value when the agent chooses actions $d_{it}$ and $e_{it}$, is defined as

$$v(d_{it}, e_{it}, s_{it}, e_{dit}) = U(d_{it}, e_{it}, s_{it}, s_{dit}) + \mathbb{E} \left[ \sum_{\tau=t+1}^{\infty} \phi(\tau-t) \left( \max_{d_{it}, e_{it}} U(d_{it}, e_{it}, s_{it}, s_{dit}) \right) d_{it}, e_{it}, s_{it}, e_{dit} \right].$$

In each period, the agent incorporates the information contained in the current states $(s_{it}, e_{it})$ to evaluate the future outcome of current-period actions: employment ($d_{it}$) and effort ($e_{it}$).
The agent’s effort policy (the optimal level of effort) as a function of the state \( s_{it} \) and the stay-or-leave decision \( d_{it} \) is given by

\[
e_{it} = c(d_{it}, s_{it}) = \begin{cases} 
\arg\max\{V(1, e_{it}, s_{it}, \varepsilon_{it+1})\}, & \text{if } d_{it} = 1, \\
0, & \text{otherwise.}
\end{cases}
\]

That is, the agent chooses the optimal level of effort \( e_{it} \), which maximizes the discounted stream of expected utility flow conditional on the current states and on staying with the firm. The temporal tradeoff of exerting effort \( e_{it} \) in (nonbonus/noncommission periods) arises between the per-period disutility \( C(e_{it}) \) in Equation (1) and the state transition \( s_{it+1} \) (updated through performance outcome \( q_{it} \) in Equation (2)) toward a higher probability of future pecuniary benefits.

The agent decides to continue with the firm if the choice-specific value of staying and exerting effort \( V(1, e_{it}, s_{it}, \varepsilon_{it+1}) \) is greater than the value of leaving \( V(0, 0, s_{it}, 0) \). That is,

\[
d_{it} = \begin{cases} 
1, & \text{if } V(1, e_{it}, s_{it}, \varepsilon_{it+1}) \geq V(0, 0, s_{it}, 0), \\
0, & \text{otherwise.}
\end{cases}
\]

The summary of the model dynamics is as follows. After observing his or her current state, an agent exerts effort and incurs disutility. Exerted effort, in combination with an idiosyncratic shock, determines the agent’s current-period sales performance. This performance affects both the current-period payoff and the probability distribution of state variables in the subsequent period. Hence, the agent’s effort helps preserve his or her state in a healthy condition, increasing the chance of receiving a monetary payoff in later periods. However, if the current state shows a limited chance of receiving future payoffs (e.g., after several periods of low performance), the agent may stop exerting effort in order to reduce disutility. Furthermore, if the value of staying becomes lower than the outside option, the agent decides to leave the firm.

### 4.4. Time Preference

The forward-looking formulation of the model naturally leads to a conceptual question: how does an agent discount the stream of future utility to derive the optimal policy? In other words, what is the agent’s time preference, the degree to which immediate utility is favored over delayed utility? The question can be addressed through varying the structure of \( \phi(j) \), the discount function in Equation (4). We consider two models of time preference: exponential discounting and quasi-hyperbolic discounting.

#### 4.4.1. Exponential Discounting

The exponential discounting model (Samuelson 1937) postulates that an agent’s discount function for the \( j \)th future period takes the form

\[
\phi(j) = \delta^j, \quad \text{for } j = 0, 1, 2, \ldots,
\]

where \( \delta \in (0, 1) \). The model implies time-consistent behavior by featuring stationary discounting (geometric decay) over expected future utility. Because of its analytical convenience, exponential discounting is frequently assumed in the economics and marketing literatures.

The dynamic optimization problem can be decomposed into an infinite sequence of single-period decisions. Assuming exponential discounting, the infinite sum of the discounted future utility flow in Equation (4) can be replaced by the subsequent-period value function such that

\[
V(d_{it}, e_{it}, s_{it}, \varepsilon_{dit}) = U(d_{it}, e_{it}, s_{it}, \varepsilon_{dit})
\]

\[
+ \mathbb{E}\left[ \max_{d_{it+1}, \varepsilon_{it+1}} V(d_{it+1}, e_{it+1}, s_{it+1}, \varepsilon_{dit+1}) \mid d_{it}, e_{it}, s_{it}, \varepsilon_{dit} \right]
\]

\[
= U(d_{it}, e_{it}, s_{it}, \varepsilon_{dit})
\]

\[
+ \mathbb{E}\left[ \max_{d_{it+1}, \varepsilon_{it+1}} \min_{\varepsilon_{it+1}} \mathbb{E}\left[ \max_{d_{it+1}, \varepsilon_{it+1}} V(d_{it+1}, e_{it+1}, s_{it+1}, \varepsilon_{dit+1}) \mid d_{it}, e_{it}, s_{it}, \varepsilon_{dit} \right] \right]
\]

Henceforth, for brevity of exposition, subscripts \( i \) and \( t \) are suppressed, and the subsequent period \((t+1)\) is denoted by a prime (’) symbol when possible.

Let \( v(d, e, s) \) denote the deterministic portion of the choice-specific value in Equation (4) (i.e., \( v(\cdot) = V(\cdot) - \varepsilon_{dit} \)), and define it as the choice-specific value function. Similarly, let \( u(d, e, s) \) denote the deterministic portion of the utility function (i.e., \( u(\cdot) = U(\cdot) - \varepsilon_{dit} \)). Assuming additive separability and serial independence of the structural errors, the preceding equation simplifies to

\[
v(d, e, s) = u(d, e, s) + \mathbb{E}\left[ \max_{d', e'} v(d', e', s') + \varepsilon_{dit}' \mid d, e, s \right].
\]

#### 4.4.2. Quasi-Hyperbolic Discounting

The quasi-hyperbolic discounting model (Phelps and Pollak 1968, Laibson 1997) posits that an agent’s discount function for the \( j \)th future period takes the form

\[
\phi(j) = \begin{cases} 
1, & \text{if } j = 0, \\
\beta^j, & \text{if } j = 1, 2, 3, \ldots,
\end{cases}
\]

where \( \delta \in (0, 1) \) is the standard discount factor, and \( \beta \in (0, 1) \) is the present-bias factor. Often referred to as the beta-delta preference, the model parsimoniously captures present bias and, thus, time inconsistency. The standard discount factor \( \delta \) captures long-term time-consistent discounting, and the present-bias
factor $\beta$ captures short-term impatience and the discontinuity between the present and the future (O’Donoghue and Rabin 1999). Note that exponential discounting is a special case of quasi-hyperbolic discounting when $\beta = 1$ (i.e., the agent is not present biased).

Given quasi-hyperbolic discounting, the choice-specific value in Equation (4) becomes

$$v(d, e, s) = u(d, e, s) + \beta \delta E \left[ \max_{d', e'} \{\tilde{v}(d', e', s') + \epsilon_d'\} \mid d, e, s \right],$$

where

$$\tilde{v}(d, e, s) = u(d, e, s) + \delta E \left[ \max_{d', e'} \{\tilde{v}(d', e', s') + \epsilon_d'\} \mid d, e, s \right].$$

Unlike the case of exponential discounting, however, the quasi-hyperbolic discounting model does not allow a recursive representation of a single value function. The flow of future utility involves an additional value function $\tilde{v}(\cdot)$ because of the agent’s time-inconsistency. Hence, the optimal choice of effort $e$ in the present becomes different from that of the future (i.e., the agent is present biased).

The structure in Equations (6) and (7) requires solving two equations for two functions. This leads to a challenge in identification, which we discuss, in detail, in the following section.

5. Identification

This section presents the formal identification arguments and proceeds in the following order. First, we discuss the primitives of static utility—performance response, pecuniary utility of wealth, and disutility of effort—and then the agents’ time-preferences—both exponential and quasi-hyperbolic. Finally, we provide an intuitive discussion of identification. The formal arguments build on those of Magnac and Thesmar (2002), which proposes exclusion restrictions to identify the standard exponential discount factor. We expand identification of time preference to consider the present-bias factor in a quasi-hyperbolic discounting model that accommodates continuous choice. The appendix provides proofs regarding formal arguments.

5.1. Static Utility

Suppose that the data consist of $(d_{it}, s_{it}, q_{it}, \psi_{it})$ for agents $i = 1, 2, \ldots, N$ over time $t = 1, 2, \ldots, T$ and that these observations are independent and identically distributed across agents. We first consider identification of the performance response function in Equation (2). The challenge in identifying the performance response of unobserved effort $e_{it}$ is in controlling for individual heterogeneity $\alpha_i$. Because one does not directly observe either construct, separately identifying effort from individual heterogeneity typically is infeasible without further restrictions. The issue becomes further complicated because an agent’s effort policy is likely a function of individual heterogeneity $\alpha_i$. That is, an agent takes into account his or her own baseline productivity when making effort decisions.

The agent’s behavior under a nonlinear compensation system provides conditions for the effort policy to be separately identified from individual heterogeneity. The idea is to exploit observations in which the optimal effort is trivially a corner solution. Consider the following assumption:

**Assumption 1 (Corner Solution).** Suppose that there exists a subset $S_a$ with a positive probability measure in the support of state variables $s$ such that if $s \in S_a$, the derivative of the value function with respect to $e$ is nonpositive—that is, $\partial v(d,e,s)/\partial e < 0$ for any $e \geq 0$.

That is, if $s$ takes a value in $S_a$, the agent exerts zero effort. The set $S_a$ exists when the agent is far above the quota (i.e., the bonus is already attained) or far below the quota (i.e., the bonus is not within reach). In either state, the agent’s additional performance provides limited gains, and, thus, the agent is better off not incurring any effort (and avoiding the associated disutility).

**Proposition 1.** Under Assumption 1, the agent’s effort policy $e_{it}$, individual heterogeneity $\alpha_i$, and the distribution of performance shock $\xi_{it}$ are identified.

**Proof.** See Section A.1 of the appendix. The proof is based on a nonparametric regression approach in a similar vein to Hu and Xin (2019). Proposition 1 governs the relation among unobserved effort, individual heterogeneity, and observed performance and stipulates the forward-looking behavior of the agents. From Proposition 1, the agent’s effort policy conditional on staying with the firm $e_{it} = e(1, s_{it})$ is identified. Even if an agent leaves the firm, the optimal effort is identified during the period in which the agent stayed with the firm.

Regarding identification of the choice-specific value function in the following lemma holds.

**Lemma 1.** Under Assumption 1, the difference in choice-specific value functions $v(1, e_{it}, s_{it}) - v(0, 0, s_{it})$ is nonparametrically identified up to scale at the optimal effort $e_{it}$ (identified in Proposition 1).

**Proof.** See Section A.2 of the appendix. The proof uses the conditional choice probability approach in Magnac and Thesmar (2002).

By the model specification in Equation (3), the value of leaving $v(0, 0, s_{it})$ is an unknown constant that does not depend on the agent’s effort choice or state variables. Hence, Lemma 1 implies that the value of
staying \( v(1, e_{1s}, s_1) \) is identified up to location and scale at the optimal effort. Given nonparametric identification of the choice-specific value function \( v \), what remains for identification are the primitives of the utility function and time preference.

5.2. Exponential Discounting Model

Identification of the exponential discounting model materializes from the exclusion restriction (Magnac and Thesmar 2002) provided by a nonlinear compensation system.

**Assumption 2 (Exclusion Restriction).** Suppose that the state variables \( s \) can be partitioned into two vectors, \( s_1 \) and \( s_2 \), where \( s_1 \) is a vector of variables that satisfies the following condition: there exists a subset \( S_1 \) in the support of \( s_1 \) such that if \( s_1 \in S_1 \), both

a. \( u(d(e, s_{12}), s_{12}) = u(d(e, s_1, s_2)), \) for any \( s_1 \) and \( s_2 \), and

b. \( v(d(e, s_{12}), s_{12}) ≠ v(d(e, s_1, s_2)), \) for some \( s_1 \) and \( s_2 \) hold.

That is, if \( s_1 \) takes a value in \( S_1 \), \( s_2 \) does not affect the present utility. In the empirical application, the variables month type and an agent’s DTQ play the role of \( s_1 \) and \( s_2 \), respectively. For example, there is no performance-based lump-sum payment in October or November, so the DTQ does not affect the per-period utility. In these months, the per-period utility depends only on the disutility of effort, which does not include \( s \). However, the future expected utilities differ according to the DTQ.

**Proposition 2.** Suppose that the agent’s true time preference follows the exponential discounting model. Under Assumptions 1 and 2, the instantaneous utility function \( u \) at the optimal effort and the discount factor \( \delta \) are nonparametrically identified.

**Proof.** See Section A.3 of the appendix. The proof uses exclusion restrictions similar to corollary 3 and proposition 4 in Magnac and Thesmar (2002).

Once \( u \) is nonparametrically identified, the parametric identification of the mean variance and reservation value within \( u \) is straightforward. Because there is no variation in pecuniary utility during nonbonus periods, \( \theta \) is identified in those months. Parameter \( \gamma \) is identified during the bonus-paying months. The remaining \( \rho \) and \( \sigma_e \) are identified using the variation in agents’ stay-or-leave decisions (see Section 5.4 for an intuitive discussion).

5.3. Quasi-Hyperbolic Discounting Model

Under the quasi-hyperbolic discounting model in Equations (6) and (7), there exist two value functions \( \nu \) and \( \nu \) and two discount factors \( \beta \) and \( \delta \). The quasi-hyperbolic discounting model is more general than the exponential discounting model because the latter is a special case of the quasi-hyperbolic discounting model when \( \beta = 1 \).

Because Lemma 1 equally applies to the quasi-hyperbolic discounting model, the choice-specific value function \( \nu \) is nonparametrically identified (up to location and scale). However, identification of \( \nu \) is not straightforward because Equations (6) and (7) form a system of equations. Multiplying Equation (7) by \( \beta \) and subtracting it from Equation (6) yield

\[
\nu(d(e, s)) = (1 - \beta)u(d(e, s)).
\]

Because \( \beta > 0 \), the preceding equation simplifies to

\[
\nu(d(e, s)) = \frac{\beta - 1}{\beta} u(d(e, s)) + \frac{1}{\beta} \nu(d(e, s)).
\]

Finally, inserting the preceding equation into Equation (6) establishes that

\[
\nu(d(e, s)) = u(d(e, s)) + \delta \max_{d'} \left[ \nu(d', e', s') + \gamma \nu(d', e', s') \right].
\]

In Equation (8), the distribution of \( e_{1d} \) and the value function \( \nu \) are known, whereas the per-period utility \( u \) and the discount factors \( \delta \) and \( \beta \) are unknown. Because this equation summarizes the system of equations, \( u \), \( \delta \), and \( \beta \) are identified if there exists a unique solution to Equation (8).

In mathematics, the structure of Equation (8) is known as a nonlinear Fredholm integral equation of the second kind (Vetterling et al. 1992, Polyanin and Manzhirov 1998, Arfken and Weber 1999). Solving the integral equation for the unknown utility function \( u(d, e, s) \) is an ill-posed inverse problem due to the maximum function and integration taken over the utility function. Because a lot of information is “integrated out” and naturally lost during the process, it is well known that the solution to this ill-posed inverse problem may not exist, or even if a solution exists, it may not be unique.19

The essence of this problem arises because of the continuity of the choice variable. If the choice variable is discrete, the integral equation in Equation (8) can be replaced by matrix algebra, and the problem is simplified to finding the inverse of the matrix. For example, Abbring and Daljord (2020) and Fang and Wang (2015), in a discrete choice setting, rely on matrix algebra to find the inverse for identification. This is not applicable to our setting—in which the choice variable is continuous—because solving for the inverse of an integral equation is ill posed. Thus, without further restrictions, the utility function and the discount factors cannot be nonparametrically identified even if the exclusion restrictions hold. Intuitively, the ill-posed problem is due to the fact that the continuous choice in the model requires the utility function to be an infinite-dimensional object (absent parametric assumptions), whereas in a discrete
choice model, the utility function is represented by a finite-dimensional vector (as in Fang and Wang 2015). Because of this difference, a finite number of exclusion restrictions is insufficient to nonparametrically identify the utility function of a continuous-choice hyperbolic discounting model.

The exponential discounting model bypasses this issue because the utility function does not enter the integral due to its recursive nature. That is, the value function for the future payoffs is identified directly from the choice probabilities. In contrast, in the quasi-hyperbolic discounting model, the utility function enters the integral as in Equation (8). This change in the value function creates complications in solving the equation, leading to uncertainty about the existence of the solution and, if it does exist, its uniqueness.

A typical solution for an ill-posed inverse problem is regularization. In a broad sense, to regularize is to provide additional assumptions that can aid the existence, uniqueness, and numerical stability of a solution. Some common examples include discretization of variables (Magnac and Thesmar 2002, Fang and Wang 2015, Abbring and Daljord 2020), eigenvalue–eigenfunction decomposition (Hu and Schennach 2008, Hu and Xin 2019), parameterization of functions, and Lasso-type penalization methods.

The parametric assumption in Equation (3) on the per-period utility function $u$ serves as a regularization to identify quasi-hyperbolic time preference under continuous choice. To illustrate, given the parameter vector $\mu = (\gamma, \beta, \rho, \sigma_v^2)$, the agent’s optimal effort (in the subsequent period) conditional on staying with the firm is

\[
e'(s|\mu) = \arg \max_e \{(\beta - 1)u(1, e, s) + v(1, e, s)\}.
\]

Note that prior to parametrization, the optimal effort for the subsequent period was intractable.

Given the extreme value distribution assumption, the future payoff component within the expectation in Equation (8), conditional on $s'$, now becomes

\[
\max_{d,e'} \{(\beta - 1)u(d', e', s'| \mu) + v(d', e', s') + \beta e'd\}
\]

\[= \beta \sigma_v \ln \left[ \exp \left( \frac{(\beta - 1)u(1,e',s'|\mu) + v(1,e',s')}{\beta \sigma_v} \right) + \exp \left( \frac{(\beta - 1)\rho + v(0,0,s')}{\beta \sigma_v} \right) \right]
\]

\[= \Lambda(s'| \mu, \beta).
\]

The expectation of the future payoff over $s'$, given the current period state and choice variables, becomes

\[
E \max_{d,e'} \{(\beta - 1)u(d', e', s'| \mu) + v(d', e', s') + \beta e')|d,e,s\}
\]

\[= \int \Lambda(s'| \mu, \beta)f(s'|d,e,s)ds'.
\]

Thus, the identification criteria in Equation (8) simplify to a function of the parameters $(\mu, \delta, \beta)$, where

\[u(d,e,s|\mu) = v(d,e,s) + \delta \int \Lambda(s'| \mu, \beta)f(s'|d,e,s)ds'.
\]

The true parameter vector $(\mu, \delta, \beta)$ solves the preceding equation $\Pi(d,e,s|\mu, \delta, \beta) = 0$ for all $(d,e,s)$. Thus, for identification, the assumption of a full-rank condition is sufficient.

Assumption 3 (Rank Condition). Denote the agent’s decision and state variables by $y = (d, e, s)$. There exists a subset $Y = \{y_j : j = 1, 2, …, J\}$ in support of $y$ such that $(\frac{\partial \Pi(y_j)}{\partial \delta}, \frac{\partial \Pi(y_j)}{\partial \beta})$ has a rank that is greater than or equal to the number of parameters.

This assumption rules out the case in which different values of parameters yield identical observations in the model. Mathematically, the assumption holds if no parameters are linearly dependent. The nonlinear nature of the model (the agent’s effort enters the mean-variance utility nonlinearly and the disutility function quadratically) readily satisfies the rank condition assumption. The sufficient conditions for Assumption 3 are formally stated in Section A.4 of the appendix.

Theorem 1. Suppose that the agent’s true time preference follows the quasi-hyperbolic discounting model. Under Assumptions 1–3, the standard discount factor $\delta$, present-bias factor $\beta$, and parameters of the utility function $\mu$ are parametrically identified.

Proof. See Section A.5 of the appendix. The proof uses the local identification approach to find the unique solution to $\Pi(d, e, s|\mu, \delta, \beta) = 0$.

5.4. Intuitive Discussion of Identification

In addition to the formal identification arguments, we discuss model identification in our empirical context. First, we provide intuition regarding the identification of static utility. Then we discuss identification regarding the discount factor(s).

A key challenge to identifying unobserved effort and utility parameters arises from limited variation in the agent’s compensation contract. There exists some variation in the contract—specifically in the quarterly and annual bonus amounts across years. Thus, variations in performance across the different compensation regimes enable identification. In addition, the relation between an agent’s sales performance and his or her state variables helps identification. The agent likely exerts more effort when close to the quota than when far from the quota. Hence, systematic differences in sales performance at different DTQs identify effort and, thus, facilitate identification of the
disutility of effort (Misra and Nair 2011, Chung et al. 2014). Suppose that there are two agents with the same states, but one has higher performance than the other. Then we can infer that the agent with higher performance has lower disutility of effort. Similarly, suppose that there are two agents, both of whom have no chance of meeting the quota (DTQ is very low), but one has higher performance than the other. Then we can infer that the agent with higher performance has higher baseline ability. The extent to which an agent over- or underperforms on the quota identifies the risk-aversion parameter. A risk-averse agent would constantly overachieve or underachieve in bonus periods, whereas a risk-neutral agent would just meet the quota. The variation in sales in the same states within an agent identifies the distribution of the performance shocks. The variation in sales with variation in performance shifters identifies the performance response parameters.

As described in Section 4.1, the parametric functional form of the agent’s payoff (specifically the mean-variance utility function) provides location and scale normalization to facilitate identification. The mean-variance utility specification implicitly presumes that the constant term of utility is zero and that the parameter associated with the mean of wealth is unity. Thus, the mean ($\rho$) and variance ($\sigma^2$) of the outside option are identified under this specification. Intuitively, if, given a level of income, salespeople are frequently leaving the firm, we can infer that the value of the outside option is high. Relatedly, the observed attrition behavior at different levels of income identifies the variance of the outside option. For example, if salespeople’s attrition behavior does not change much with changes in income, we can infer high variance in the value of the outside option. Naturally, the variation in reservation shifters identifies the corresponding parameters.

As explained in Section 5.2, an agent’s DTQ in nonbonus periods functions as an exclusion restriction to identify discount factor(s). Suppose that there are two agents with the same characteristics who display the same behavior (and, thus, performance) at the end of the year (final period of a compensation cycle). However, suppose that in nonbonus periods, one agent performs better than the other, even though both are in the same state (DTQ). We can infer that the agent with high performance in nonbonus periods has a higher discount factor (or a lower discount rate). The hyperbolic discounting model, under the functional form specification of utility, is identified if there exist more than two periods with exclusion restrictions. The performance of an exponential discounter would be more consistent and smoother throughout the year compared with that of a hyperbolic discounter.

**6. Estimation**

The estimation procedure follows the full-solution method (Rust 1987) using maximum likelihood rather than the conditional-choice probability approach (Hotz and Miller 1993, Bajari et al. 2007) because the two-step estimation procedure can generate biases if the state variables in the policy function are correlated with the first-stage errors. In addition, the maximum likelihood approach has the minimum variance achievable by a consistent and asymptotically normally distributed estimator.

**6.1. Individual Likelihood**

Given the value function in Equation (4) and the empirical specification of the per-period utility function in Equation (3), one can obtain the expected value function through the inner loop in the conventional nested fixed-point algorithm such that

$$EV(d, e, s) \equiv E_{d, e, s}[V(s', e'; d, e, s)]$$

$$= \int_{\xi} \sigma^2 \ln \left( \sum_{d \in \{0,1\}} \exp \left[ \frac{\max\{u(d', e', s')}{\sigma^2_{\xi}} \right] \right) d\xi'.$$

Then the choice probability of stay or leave $\pi_{de(0,1)}$, conditional on the agent’s state, is obtained by solving the agent’s dynamic optimization problem

$$\pi_{dit} = \Pr(d_{it} | \pi_{dit})$$

$$= \frac{\exp[(\max_{e \in C} \{u(d, e, s) + \phi(1)EV(d, e, s)})/\sigma^2_{\xi}]}}{\sum_{d \in \{0,1\}} \exp[(\max_{e \in C} \{u(d, e, s) + \phi(1)EV(d, e, s)})/\sigma^2_{\xi}]}}.$$  (9)

In the process, the optimal effort $e_{it}$, given agent $i$’s state in period $t$, is inferred by the level at which the expected value function is maximized. The attained effort enters the performance response function in Equation (2).

By combining Equations (2) and (9), one can compute the likelihood of the agent’s observations. Given the history of an agent with observations over $T$ periods, the agent’s likelihood is

$$L_t(\Omega, q_{it}, d_{it}, s_{it}) = \prod_{t=1}^{T} \left( \phi_{\xi, i}(\ln(q_{it}) - \ln(q_{it})); \pi_{dit}) \right)^{d_{it}} \cdot \pi_{dit}(1-d_{it}),$$

where the vector $\Omega = \{\delta_i, \beta, \gamma_i, \theta_i, \rho_i, \sigma_e, \alpha_e, \sigma_\xi\}$ is the set of parameters of time preference and the utility and performance response functions, $d_{it}$ denotes the observed stay-or-leave decision, $q_{it}$ is the observed performance, and $\phi_{\xi,t,i}$ denotes the probability density function of a normal distribution with mean zero and variance $\sigma^2_{\xi}$. 

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6.2. Unobserved Heterogeneity

Discrete segments accommodate unobserved heterogeneity (Kamakura and Russell 1989). Assume that salesperson \( i \) belongs to one of \( K \) segments \( k \in \{1, \ldots, K\} \) with relative probabilities

\[
m_k = \frac{\exp(\lambda_k)}{\sum_{k'} \exp(\lambda_{k'})}.
\]

Let \( L_{it} = L(\Omega_k \mid k; q_{it}, d_{it}, s_{it}) \) be the likelihood of parameters for individual \( i \) at time \( t \), conditional on unobservable segment \( k \), given the agent’s data. Then the likelihood of the segment-level parameters on observing an individual’s history is

\[
L_k(\Omega_k; q_{it}, d_{it}, s_{it}) = m_k \left( \prod_{t=1}^{T} L_{it} \right).
\]

By summing over all the unobserved states \( k \in \{1, \ldots, K\} \), the overall likelihood of individual \( i \) becomes

\[
L(\Omega; q_{it}, d_{it}, s_{it}) = \sum_{k=1}^{K} L_k(\Omega_k; q_{it}, d_{it}, s_{it}),
\]

where \( \Omega = \{\Omega_1, \ldots, \Omega_K\} \) contains the segment-level parameters. Hence, the log-likelihood over the \( N \) sample of individuals becomes

\[
\sum_{i=1}^{N} \ln(L(\Omega; q_{it}, d_{it}, s_{it})) = \sum_{i=1}^{N} \ln \left( \sum_{k=1}^{K} m_k \left( \prod_{t=1}^{T} L_{it} \right) \right).
\]

### 7. Results

This section presents the results in the following order. First, we show the results of the exponential and quasi-hyperbolic discounting models and discuss their implications. Then, we show how changes in the compensation plan have led to sales force selection across heterogeneous agents. Next, we show the results of counterfactual simulations that address the substantive questions of this study—how sales management instruments (compensation, recruiting/termination, and training policies) affect the performance and selection of salespeople. Finally, we compare simulated performance and attrition with actual outcomes in the post-data-analysis period—accompanied by real changes in the firm’s sales management instruments—to validate the accuracy of our model.

#### 7.1. Parameter Estimates

Table 5 shows the parameter estimates of the exponential and quasi-hyperbolic discounting models. Based on the Bayesian information criterion (BIC), the three-segment model shows the best fit.\(^{20} \)

Regarding time preference in the exponential discounting model, the discount factors \( (\delta) \) are 0.895, 0.975, and 0.983, respectively, for segments 1, 2, and 3. The range of the standard discount factor is consistent with behavioral and empirical studies on time preference (Frederick et al. 2002, Yao et al. 2012,

### Table 5. Parameter Estimates

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Exponential discounting</th>
<th>Quasi-hyperbolic discounting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Segment 1</td>
<td>Segment 2</td>
</tr>
<tr>
<td>Time preference</td>
<td></td>
<td></td>
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<td>Standard discount factor</td>
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<td>Present-bias factor</td>
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<td>Utility function</td>
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<td>Reservation value</td>
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<tr>
<td>Baseline</td>
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<td>Midlevel (tenure three to seven years)</td>
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<td>Senior (tenure &gt; seven years)</td>
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<td>−0.270</td>
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<td>Higher education</td>
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<td>Standard deviation of utility shock</td>
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<td>Performance response function</td>
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<td>Baseline productivity</td>
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<td>11,047.392</td>
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Notes. Significance (at the 0.05 level) appears in bold. Standard errors are approximated by inverse of the Hessian of the log-likelihood and are omitted from the table for brevity.
Chung et al. (2014). In the quasi-hyperbolic discounting model, the standard discount factors ($\delta$) are 0.996, 0.976, and 0.994, respectively, and the present-bias factors ($\beta$) are 0.477, 0.999, and 0.980, respectively, for segments 1, 2, and 3. Figure 4 is a graphic illustration of time preference (and, thus, the amount of discounting toward the future) by segment.21 The solid lines represent exponential discounting, and the dotted lines represent quasi-hyperbolic discounting. Segment 1 shows myopic and present-biased behavior, and segments 2 and 3 show forward-looking and time-consistent discounting behavior.

The quasi-hyperbolic discounting model is a more general structure than the exponential discounting model. Furthermore, the BIC values of the two models indicate that the quasi-hyperbolic discounting model fits the data better, implying that some sales agents are present biased in their time preferences. Hence, we use the results of the quasi-hyperbolic discounting model for inference. For the structural parameters of the utility function, the disutility parameter ranges from 0.556 to 23.911. The disutility parameter is small for segment 3 (hereafter referred to as the high type), representing the agents’ ease and flexibility in exerting effort. Conversely, the estimate is large for segments 1 and 2 (hereafter referred to as the low and moderate types). Hence, the following pattern appears in terms of segmentation. Segments 2 and 3 exhibit forward-looking behavior, which is expected of moderate- to high-performing agents who seek the end-of-year bonus and overachievement commission. The low-type agents, by contrast, show myopic behavior.

The reservation value is low for segments 1 and 2, reflecting limited outside opportunities for these types of agents, and high for segment 3, implying the various potential opportunities outside the firm. For reservation value shifters, education and tenure are statistically insignificant, potentially reflecting the nature of personal selling, in which interpersonal and relational skills are more important than such observable characteristics.22

Regarding the parameters of the performance response function, tenure (both the midlevel and senior dummy variables) has a positive effect on performance. In addition, training improves performance, but the interaction effect of midlevel and senior dummies with training is negative and significant. Hence, training does not benefit senior salespeople as much as it does junior salespeople.

7.2. Selection

The change in the firm’s compensation plan likely has led to the selection of its sales force. Table 6 shows the share of the three segments and their descriptive characteristics across the full three years of the data. Segment 1, the myopic low type, has the smallest share, 13.29%; segments 2 and 3 represent bigger shares, 64.24% and 22.47%, respectively. Consistent with the parameter estimates in Table 5, segment 3 achieves the highest performance, with the largest portion meeting the annual quota. The average base salary is high for this segment, reflecting their tenure. Segment 2, the forward-looking moderate type, falls short on performance compared with segment 3 and

![Figure 4. Time Discounting by Segment](image)

*Notes.* The solid lines represent exponential discounting, and the dotted lines represent hyperbolic discounting, respective to each segment. The $y$-axis depicts the rate of discounted future value (as compared with the present value), and the $x$-axis depicts time horizon (months forward).
has lower tenure. The myopic low type, segment 1, falls short in every performance dimension and exhibits a stark difference in annual variable pay compared with the other segments.

In terms of selection incurred over time, Table 7 shows the segment portfolio (in percentages) of the total sales force by each year end—reflecting how the portfolio of salespeople has changed over time. The share of segment 2, the forward-looking moderate type, has constantly increased. In contrast, the shares of segments 1 and 3 have decreased over the years. This reflects the frequent quitting within these segments, likely because of insufficient compensation from lack of performance for segment 1 and good outside opportunities for segment 3.

### 7.3. Counterfactual Simulations

This section shows the results of several counterfactual simulations that address the key substantive question of this study: how can a firm manage, motivate, and sustain a healthy sales force using the sales management instruments outlined in Figure 1? The counterfactuals evaluate agents’ performance and selection according to changes in (1) compensation structure, (2) training hours, and (3) recruiting and termination policies.

The counterfactuals suppose that the firm is undertaking its policy design at the beginning of 2018 (i.e., following the data observation period) with its remaining portfolio of salespeople (n = 400). The basis for the changes is the 2017 policy. For each new regime, we simulate 200 paths per each individual—segment pair using the parameter estimates of the quasi-hyperbolic discounting model. Then we allocate individuals into each segment based on segment probabilities. Finally, we aggregate performance and selection.

#### 7.3.1. Alternative Compensation Structures

The challenge in designing a compensation system is to determine the optimal ratio of fixed and variable pay. The theory predicts that when a firm increases the portion of fixed pay, employee attrition likely decreases. But how would heterogeneous salespeople react differently to the change in terms of both performance and selection? Hence, the first counterfactual exercise examines a change in fixed versus variable pay while keeping other components constant. Table 8 depicts performance, attrition, and compensation under the new regimes.

First, we increase the base salary by 5%, 10%, and 15% and keep everything else constant. As anticipated, the attrition rate decreases across all segments. However, a notable aspect is that sales performance also decreases. This is driven mainly by the retention effect: being granted higher rent, the low-performing agents, who otherwise would have left the firm, are now more likely to stay with the firm. The retention effect is stronger for the low types, reflected by the more pronounced decrease in sales performance. Next, we increase the bonus amount by 5%, 10%, and 15% and keep everything else constant. Again, employee attrition decreases; however, compared with the case of an increase in base salary, the reduction is smaller. Moreover, the effect on sales performance is positive, especially with the high-type agents, because an increase in the bonus amount helps motivate these agents to a greater extent.

The analyses demonstrate the tradeoff between adjusting fixed versus variable pay on employee performance and selection. Although increasing the fixed salary could serve as a simple remedy to reduce employee attrition, it could, on average, hurt the overall performance of the sales force. In contrast, an increase in variable pay does not harm performance but has a smaller effect on employee attrition. The effect of policy changes applies heterogeneously

### Table 6. Segment Characteristics

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segment size, %</td>
<td>13.29</td>
<td>64.24</td>
<td>22.47</td>
</tr>
<tr>
<td>Monthly base salary, USD</td>
<td>1,424.15</td>
<td>1,485.80</td>
<td>1,645.88</td>
</tr>
<tr>
<td>Annual variable pay, USD</td>
<td>671.46</td>
<td>4,829.50</td>
<td>10,114.43</td>
</tr>
<tr>
<td>Tenure, years</td>
<td>2.95</td>
<td>3.99</td>
<td>4.99</td>
</tr>
<tr>
<td>Sales training, hours per year</td>
<td>2.45</td>
<td>3.35</td>
<td>4.38</td>
</tr>
<tr>
<td>Higher education</td>
<td>0.95</td>
<td>0.93</td>
<td>0.94</td>
</tr>
<tr>
<td>Annual performance, %</td>
<td>74.42</td>
<td>92.50</td>
<td>112.19</td>
</tr>
<tr>
<td>Meet 100% quota, %</td>
<td>22.15</td>
<td>34.55</td>
<td>74.87</td>
</tr>
<tr>
<td>Q1</td>
<td>15.57</td>
<td>31.47</td>
<td>83.33</td>
</tr>
<tr>
<td>Q2</td>
<td>4.00</td>
<td>28.94</td>
<td>86.57</td>
</tr>
<tr>
<td>Q3</td>
<td>1.74</td>
<td>31.11</td>
<td>91.46</td>
</tr>
<tr>
<td>Segment size, %</td>
<td>13.29</td>
<td>64.24</td>
<td>22.47</td>
</tr>
</tbody>
</table>

**Note.** The numbers are approximate for confidentiality.

### Table 7. Selection of Sales Force over Time

<table>
<thead>
<tr>
<th>Years</th>
<th>N</th>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beginning of 2015</td>
<td>303</td>
<td>10.26</td>
<td>62.73</td>
<td>27.01</td>
</tr>
<tr>
<td>End of 2015</td>
<td>330</td>
<td>8.29</td>
<td>63.34</td>
<td>28.37</td>
</tr>
<tr>
<td>End of 2016</td>
<td>367</td>
<td>8.71</td>
<td>66.17</td>
<td>25.12</td>
</tr>
<tr>
<td>End of 2017</td>
<td>400</td>
<td>6.88</td>
<td>66.53</td>
<td>26.59</td>
</tr>
</tbody>
</table>
across segments, which affects the resulting portfolio of the remaining salespeople.

7.3.2. Sales Training. The next counterfactual simulation involves changes in sales training. As discussed in Section 7.1, sales training positively affects productivity but mostly for junior salespeople. The increase in productivity affects not only current-period utility but also future outcomes, which bring about changes in the dynamic optimization of effort over time. To evaluate the role of sales training on performance and selection, we provide 6, 12, and 24 hours of sales training in January for all agents. Table 9 shows the results.

As anticipated, sales training leads to an increase in performance across all segments. In addition, the employee attrition rate decreases across all segments. The general trend of providing sales training is similar to that of increasing the bonus amount: training helps agents obtain better performance, which, in turn, raises the probability of attaining the bonus and, thus, an increase in compensation.

Although the counterfactual results shown in the preceding two cases provide a practical tool for evaluating alternative compensation structures and training programs, in practice, managers often face a limited budget for implementing a new sales management policy. Therefore, the objective becomes finding a policy that offers the best possible outcome subject to the budget constraint. To conduct such cost-benefit comparison requires normalizing the cost factor because each policy entails a different cost to implement (in both compensation amount and training investment). Hence, the following counterfactual analysis evaluates a scenario in which the allocated budget is held fixed at $2,400 per salesperson across all policies. This amount is about 10% of total annual compensation, including fixed and variable pay.

Table 10 depicts the relative effectiveness of corresponding policies: increasing salary by 12.60%, increasing bonus by 13.75%, and providing 19.50 hours of training, which all satisfy the given annual budget of $2,400 per salesperson. Regarding sales training, both the fixed investment of providing training sessions at $37/hour and an increase in compensation from better performance are included as costs. Similar to the findings from the previous counterfactuals, a fixed salary is effective for employee retention, whereas variable pay and sales training are effective for performance growth. Regarding the latter two instruments, variable pay is used to increase the performance of high-type salespeople (by providing greater upside potential),

Table 8. Counterfactual Simulation: Compensation Structure

<table>
<thead>
<tr>
<th>Counterfactual simulation</th>
<th>Total</th>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase salary: 5%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>-0.024</td>
<td>-0.069</td>
<td>-0.010</td>
<td>-0.037</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.891</td>
<td>-1.675</td>
<td>-0.622</td>
<td>-1.197</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>3.948</td>
<td>4.968</td>
<td>4.146</td>
<td>3.210</td>
</tr>
<tr>
<td>Increase salary: 10%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>-0.029</td>
<td>-0.091</td>
<td>-0.002</td>
<td>-0.069</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-1.679</td>
<td>-3.331</td>
<td>-1.162</td>
<td>-2.179</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>7.911</td>
<td>9.931</td>
<td>8.317</td>
<td>6.422</td>
</tr>
<tr>
<td>Increase salary: 15%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>-0.044</td>
<td>-0.137</td>
<td>-0.011</td>
<td>-0.080</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-2.393</td>
<td>-4.911</td>
<td>-1.681</td>
<td>-2.941</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>11.862</td>
<td>14.885</td>
<td>12.463</td>
<td>9.645</td>
</tr>
<tr>
<td>Increase bonus: 5%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>2.111</td>
<td>-0.005</td>
<td>1.762</td>
<td>4.378</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.314</td>
<td>-0.054</td>
<td>-0.161</td>
<td>-0.902</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>3.538</td>
<td>0.037</td>
<td>3.460</td>
<td>4.894</td>
</tr>
<tr>
<td>Increase bonus: 10%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>3.786</td>
<td>-0.010</td>
<td>3.442</td>
<td>7.048</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.587</td>
<td>-0.097</td>
<td>-0.305</td>
<td>-1.681</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>6.950</td>
<td>0.075</td>
<td>7.177</td>
<td>8.867</td>
</tr>
<tr>
<td>Increase bonus: 15%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>5.909</td>
<td>-0.010</td>
<td>5.840</td>
<td>9.653</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.856</td>
<td>-0.103</td>
<td>-0.489</td>
<td>-2.348</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>11.186</td>
<td>0.113</td>
<td>12.214</td>
<td>12.972</td>
</tr>
</tbody>
</table>

Note. The change in average performance and attrition rate is in percentage points; the change in compensation amount is in percentages.
and sales training supports low and moderate types (through an increase in base productivity). Hence, the analysis demonstrates how the model of agent’s behavior can be used to conduct a cost-benefit analysis and, thus, can support firms in deciding the sales management policy that best suits their desired outcome under a constrained budget.

Finally, we elaborate on the risk of a simple cost-wise comparison across different sales management instruments. Without the model, a manager may have conceived a 19.5-hour sales training to be cost-wise equivalent to a 4% annual salary increase. However, the analysis reveals that because of the increase in compensation, the figures are closer to a 12.60% salary increase. The discrepancy arises because of changes in salespeople’s behavior: training increases salespeople’s productivity, which improves their performance, and, thus, the firm pays more compensation. This example illustrates the limitation of a simple cost-wise comparison based on accounting figures and highlights the value of a structural model that captures the causal change in an agent’s behavior under alternative scenarios.

### Table 9. Counterfactual Simulation: Sales Training

<table>
<thead>
<tr>
<th>Counterfactual simulation</th>
<th>Total</th>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase sales training: 6 hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>1.831</td>
<td>0.519</td>
<td>2.330</td>
<td>1.188</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.269</td>
<td>-0.167</td>
<td>-0.201</td>
<td>-0.525</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>1.992</td>
<td>0.205</td>
<td>2.901</td>
<td>0.823</td>
</tr>
<tr>
<td>Increase sales training: 12 hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>3.598</td>
<td>1.066</td>
<td>4.499</td>
<td>2.528</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.538</td>
<td>-0.278</td>
<td>-0.420</td>
<td>-1.027</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>4.049</td>
<td>0.434</td>
<td>5.854</td>
<td>1.753</td>
</tr>
<tr>
<td>Increase sales training: 24 hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>6.596</td>
<td>2.193</td>
<td>8.079</td>
<td>4.978</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-1.101</td>
<td>-0.629</td>
<td>-0.911</td>
<td>-1.925</td>
</tr>
<tr>
<td>Compensation amount</td>
<td>7.675</td>
<td>1.041</td>
<td>10.987</td>
<td>3.461</td>
</tr>
</tbody>
</table>

Note. The change in average performance and attrition rate is in percentage points; the change in compensation amount is in percentages.

### Table 10. Counterfactual Simulation: Cost–Benefit Analysis

<table>
<thead>
<tr>
<th>Counterfactual simulation</th>
<th>Total</th>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase salary: 12.60%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>-0.035</td>
<td>-0.096</td>
<td>-0.010</td>
<td>-0.072</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-2.070</td>
<td>-4.143</td>
<td>-1.464</td>
<td>-2.576</td>
</tr>
<tr>
<td>Increase bonus: 13.75%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>5.278</td>
<td>-0.013</td>
<td>5.098</td>
<td>8.965</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.783</td>
<td>-0.108</td>
<td>-0.432</td>
<td>-2.185</td>
</tr>
<tr>
<td>Increase sales training: 19.50 hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>5.613</td>
<td>1.765</td>
<td>6.917</td>
<td>4.179</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>-0.883</td>
<td>-0.479</td>
<td>-0.725</td>
<td>-1.575</td>
</tr>
</tbody>
</table>

Notes. All alternative policies involve a cost of $2,400 per salesperson (about 10% of total annual compensation, including fixed and variable pay). The changes are in percentage points.

7.3.3. Recruiting and Termination Policy. A firm can induce selection of its sales force through its recruiting and termination policies. We consider two cases: (1) changes in the firm’s recruiting policy and (2) changes in its termination policy.

The recruiting policy relates to the type of salespeople that the firm should target during its hiring process. First, suppose that the firm can observe the agents’ latent types. Should the firm focus on targeting the high types, who are more likely to be skilled but require greater compensation to keep? Alternatively, should the firm target the moderate or low types at lower costs? To evaluate the outcomes of the recruiting policy, we simulate the firm to hire 50 of each type (low, moderate, and high) and compare the differences in performance and attrition over a five-year horizon. Figure 5(a) depicts the annual performance (solid lines) and cumulative attrition rate (columns) by segment. As anticipated, the high types show better performance than the low types. However, the high types’ high performance comes at a cost: these agents are more apt to depart the firm because of better outside opportunities, leaving their...
territories vacant. Hence, in Figure 5(b), we report the attrition-adjusted performance, which accounts for territory vacancies (treated as zero sales). Although, in the short run, hiring high-type agents leads to greater performance, in the long run, territory vacancy can be detrimental to the firm’s objectives. Therefore, without any changes in effort to retain high-type salespeople, simply recruiting a large number of them can have limited positive effects on the firm’s sales performance.26

This policy, however, is not directly applicable in practice because firms cannot observe the agents’ hidden types. Hence, we examine a scenario in which the firm possesses information about the candidates’ tenure, which provides ex ante understanding of the agents’ experience and, thus, the underlying type. The dilemma is whether to poach rivals’ experienced salespeople, who are more likely to be pre-equipped with sales skills but require greater compensation to hire, or to target inexperienced rookies, who require a lower base salary and have the potential to be trained from the outset of their career.27 Hence, to answer this question, we simulate the firm to hire 50 salespeople—either experienced (tenure of three to seven years) or rookies (tenure of zero to two years).28 To capture the nurturing opportunity, the firm provides the rookie salespeople with a 24-hour sales training each year (equivalent to the salary difference with experienced salespeople). Figure 6(a) shows the performance and attrition results. As expected, experienced salespeople perform better than rookies in the short run. However, the gap narrows as sales training accumulates for the rookies, and they eventually outperform the experienced salespeople. Further, this gain in productivity lowers the rookies’ attrition rate, and as shown in Figure 6(b), rookie salespeople exhibit better net productivity (i.e., attrition-adjusted performance) by the fifth year. Therefore, a firm should consider the outcome priority (e.g., short-versus long-term performance) and the associated efforts (e.g., nurturing and retention) when setting its recruitment policy.

On the flip side of recruiting is the firm’s policy for terminating its salespeople. In most nations, including Turkey, firm-initiated employee termination is limited because of labor force regulations. Hence, to terminate a salesperson by discretion, the firm must provide a leave package to which the employee agrees. We evaluate the effect of a leave package by providing a lump sum of $4,500, $9,000, and $18,000 (equivalent to a 3-, 6-, and 12-month base salaries, respectively) that agents can opt into. Table 11 shows that the leave package affects the low- and moderate-type agents (segments 1 and 2) more because the marginal value of the package is higher for these segments. The firm’s average sales increases because agents with less potential tend to be the ones to accept the package and leave. Hence, strategically providing leave packages can potentially lead to better outcomes and to the firm’s desired selection of salespeople.

7.4. Field Validation
In the beginning of 2018, the focal firm, based on the results of the counterfactual analyses, raised its bonus amount by 20% and implemented an additional 12 hours of training (six hours each in the first and second halves of the year). To validate the accuracy of our model, we obtain the performance and attrition records under the new regime (January–June 2018)
and compare the actual data and the counterfactual outcomes, which are simulated based on changes in the sales management instruments.

Figure 7 compares the actual (solid line) and projected (dotted black line) performance outcomes over the six-month period. The model simulation projects the general trend, though it is less cyclical. Overall, the projected performance results fit the actual outcomes well with a mean absolute percentage error of 0.97% on aggregate and 3.74% in monthly sales. In terms of employee attrition, the model predicts that 11 salespeople would leave the firm during the six-month period. In reality, 9 salespeople actually left the firm.

The comparison shows the competence of the model to predict and, thus, to evaluate the outcomes under a new policy that includes multiple sales management instruments. We also simulate performance outcomes in the case that the firm had not made any changes (i.e., kept the 2017 sales management strategy) to its sales management instruments. The results (dotted gray line) show that the firm’s performance increased by 8.51% as a result of the changes in its sales management.

Organizations should approach with caution when changing their sales management strategy because it can be quite costly. The cost includes not only the direct cost of amending administrative functions but also opportunity costs and the cost of “getting it wrong.” For example, when an organization initially gives a bonus but takes it away later, salespeople’s performance can be lower than having not given the bonus in the first place because of erosion in intrinsic motivation (Lepper et al. 1973, Chung and Narayandas 2017). In addition, the organization’s management can lose credibility with its employees when management policies repeatedly change. Hence, the framework and model of this study provide rigorous yet practical means for organizations to foresee the result of a change in alternative sales management strategies.

Table 11. Counterfactual Simulation: Termination Policy

<table>
<thead>
<tr>
<th>Counterfactual simulation</th>
<th>Total</th>
<th>Within segment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Segment 1</td>
</tr>
<tr>
<td>Leave package: $4,500 (3-month salary)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>0.009</td>
<td>0.000</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>0.854</td>
<td>1.129</td>
</tr>
<tr>
<td>Leave package: $9,000 (6-month salary)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>0.030</td>
<td>0.004</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>1.752</td>
<td>2.105</td>
</tr>
<tr>
<td>Leave package: $18,000 (12-month salary)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average performance</td>
<td>0.056</td>
<td>0.030</td>
</tr>
<tr>
<td>Attrition rate</td>
<td>3.796</td>
<td>4.097</td>
</tr>
</tbody>
</table>

Note. The changes are in percentage points.
8. Conclusion
Managing a sales force is an intricate task with multidimensional outcomes. If properly managed, organizations can induce greater performance from their sales force while retaining their top performers. This study develops and estimates a dynamic structural model of comprehensive response to multiple sales management instruments, including compensation, training, and recruiting/termination policies. The model takes into consideration many elements that constitute a realistic working environment: allocation of continuous effort, forward-looking behavior, present bias, effectiveness of sales training, and employee attrition. Substantively, the study provides guidance to firms on (1) evaluating the differential outcomes of various compensation policies, (2) assessing the selection of different types of employees in relation to changes in recruiting and termination policies, and (3) addressing the value of sales training.

The following summarizes the study’s results. An increase in fixed salary positively affects employee retention but may decrease aggregate sales because low-type agents, who otherwise would have left the firm, are likely to stay. In contrast, an increase in variable pay enhances sales performance but has limited effect on employee retention. Because of the focal firm’s selection process over time, high performers steadily left the firm, and middle performers remained. However, if the firm was to focus mainly on recruiting high-performing, experienced salespeople, sales would increase in the short term but would likely decrease in the long term because of territory vacancies created by salespeople’s attrition. Hence, firms should focus on retention endeavors along with their recruiting efforts of high performers. In addition, providing adequate leave packages can lead to an appropriate selection of salespeople to maintain a healthy sales force. Furthermore, sales training, a novel management instrument that both academics and practitioners have often overlooked, is an effective long-term performance driver that aids salespeople in their early careers to improve their sales and, in turn, their retention. A field validation, comparing post-analysis actual and counterfactual outcomes, verifies the accuracy of the model. The field validation supports the practical applicability of the model in the real world—a model that can predict changes in behavior (and, thus, sales and employee attrition outcomes) under various sales management strategies using multiple instruments.

Methodologically, the study introduces a new insight into the marketing and economics literatures by providing a formal proof regarding the identification of discount factors in a hyperbolic discounting model, accompanying continuous and unobserved choices. The key to identification is the aggregation of performance over a specific time horizon when evaluating compensation: an agent’s distance to the quota for obtaining a bonus payment (in nonbonus periods) serves as an exclusion restriction that affects only future utility and not current utility. The study provides conditions under which both exponential and hyperbolic discounting models are identified and, through the empirical application, finds evidence of present bias in salespeople’s behavior.

This study has some limitations that open avenues for future research. First, it does not consider multidimensional effort regarding different products (Chung et al. 2020) or customer types (Kim et al. 2019),
by which agents can exhibit dynamic substitution across products, customers, or both. For example, in the early periods of a quota-evaluation cycle, an agent might focus on high-ticket products that, if sold, could satisfy a large portion of the agent’s quota. However, as periods pass, an agent might gradually shift to low-ticket and easy-to-sell products. Second, free goods as a sales promotion tool, which is common in the pharmaceutical industry, can induce additional dynamics in a sales agent’s behavior. Although free goods reduce the agent’s short-term returns on performance, they can induce greater long-term outcomes. We thus, train, and, thus, maintain a healthy sales force to achieve their desired outcomes.

Relatedly, an agent’s effort decision, in addition to the immediate short-term effect, can also have a long-term effect on sales through augmented customer relationships. Finally, this study considers time-invariant unobserved heterogeneity; however, time-variant unobserved factors (Arcidiacono and Miller 2011, Hu and Shum 2012, Chou et al. 2019) may affect the agent’s effort decision. Although not addressed in this study because of data limitations and model parsimony, the aforementioned topics would provide exciting avenues for future research.

In summary, this study offers a comprehensive, practical, yet rigorous application for understanding the roles of multiple sales management instruments—compensation, training, recruiting, and termination—in the selection and performance of salespeople. We believe that the results will guide organizations in their sales management practices to help recruit, compensate, train, and, thus, maintain a healthy sales force to achieve their desired outcomes.

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Appendix.
A.1. Proof of Proposition 1
Because the agent chooses effort after observing the state variables \(s_{it}\), individual heterogeneity \(a_i\), and the utility shock \(\epsilon_{dit}\), the agent’s optimal effort policy \(e_{it}\) is a function of \(s_{it}, a_i\) and \(\epsilon_{dit}\) (i.e., \(e_{it} = e(s_{it}, a_i, \epsilon_{dit})\)). However, \(\epsilon_{dit}\) does not affect effort because it is invariant to the effort choice conditional on the stay-or-leave decision \(d_{it}\). Hence, the performance response function can be represented as

\[
\ln(q_{it}) = \alpha_i + e(s_{it}, a_i) + \xi_{it},
\]

where \(q_{it}\) and \(s_{it}\) are observed but \(a_i\) and \(\xi_{it}\) are not. By Assumption 1, when \(s_{it} \in S_a\) the value function is a decreasing function of effort. Hence, the optimal effort is zero (i.e., \(e(s_{it}, a_i) = 0\) for \(s_{it} \in S_a\)). Therefore, we have \(\ln(q_{it}) = \alpha_i + \xi_{it}\). Independence between \(\xi_{it}\) and \(s_{it}\) implies

\[
E(\ln(q_{it}) | s_{it} \in S_a) = \alpha_i + E(\xi_{it} | s_{it} \in S_a) = \alpha_i,
\]

from which \(\alpha_i\) is identified.29

Once \(\alpha_i\) is identified (from observations \(s_{it} \in S_a\)), the performance response (when \(s_{it} \notin S_a\)) takes the form of a nonparametric regression with a known intercept: \(e(s_{it}, a_i)\) is a regression function of \(\ln(q_{it}) - \alpha_i\) on \(s_{it}\) and \(a_i\). Thus, the optimal effort \(e_{it}\) is identified from \(E(\ln(q_{it}) - \alpha_i | s_{it}, a_i)\) using nonparametric regression methods. The distribution of the residuals is a consistent estimator for the distribution of \(\xi_{it}\). □

A.2. Proof of Lemma 130
Consider an agent with \((s_{it}, \epsilon_{0it}, \epsilon_{1it})\). The agent chooses to stay with the firm only if

\[
v(1, e, s_{it}) + \epsilon_{1it} \geq v(0, 0, s_{it}) + \epsilon_{0it}.
\]

Although \(\epsilon_{0it}\) and \(\epsilon_{1it}\) are unobserved, their joint distribution is assumed to be known up to the scale parameter \(\sigma_e\). Thus, the probability of staying with the firm can be written as

\[
Pr(d_{it} = 1 | s_{it}) = Pr\left(\frac{v(1, e, s_{it}) - v(0, 0, s_{it})}{\sigma_e} \geq \frac{\epsilon_{0it} - \epsilon_{1it}}{\sigma_e}\right) = F\left(\frac{v(1, e, s_{it}) - v(0, 0, s_{it})}{\sigma_e}\right),
\]

where \(F(\cdot)\) is the cumulative distribution function of \((\epsilon_{0it} - \epsilon_{1it})/\sigma_e\). Because the probability of staying with the firm can be computed from the observable data \((d_{it}, \epsilon_{dit})\), one can obtain the difference in choice-specific value function via

\[
v(1, e, s_{it}) - v(0, 0, s_{it}) = \sigma_e F^{-1}(Pr(d_{it} = 1 | s_{it})).
\]

A.3. Proof of Proposition 231
The value functions at states \((s_{it} \in S_t, \tilde{s}_2)\) and \((s_{it} \in S_t, \tilde{s}_2)\), which satisfy Assumption 2, can be evaluated such that

\[
v(d, e, s_{it}, s_2) = u(d, e, s_{it}, s_2) + \epsilon^d \max_{d', s'} v(d', e', s') + \epsilon^d |d, e, s_{it}, s_2|.
\]

(A.1)

\[
v(d, e, s_{it}, \tilde{s}_2) = u(d, e, s_{it}, \tilde{s}_2) + \epsilon^d \max_{d', s'} v(d', e', s') + \epsilon^d |d, e, s_{it}, \tilde{s}_2|.
\]

(A.2)
Subtracting Equation (A.2) from (A.1) cancels out the per-period utility:

\[ v(d,c,s_1,s_2) - v(d,c,s_1,s_2) = \delta \mathbb{E} \left[ \max_{d',c'} \left\{ v(d',c',s) + \epsilon'_d | d, c, s, s_2 \right\} \right] - \mathbb{E} \left[ \max_{d',c'} \left\{ v(d',c',s') + \epsilon'_d | d, c, s, s_2 \right\} \right]. \]

From Lemma 1, \( v(1, c, s_0) \) is identified up to location and scale, and, thus, the difference in value functions (on the left-hand side) is identified up to scale. Using the identified difference in value functions and the law of motion, the difference in expected value functions (on the right-hand side) can be computed up to scale. Because the unidentified scale parameter on both sides cancels out, the discount factor \( \delta \) is uniquely identified. The per-period utility \( u \) is identified from either (A.1) or (A.2) given the value function and the discount factor. The scale of the per-period utility function is normalized by the functional form of the mean-variance utility. □

**A.4. Sufficient Conditions for Assumption 3 (Rank Condition)**

Observe that the derivatives of \( \Pi \) with respect to the parameters are given by

\[
\begin{align*}
\frac{\partial \Pi(y | \omega)}{\partial y} &= -\var{W | y} - \delta(\beta - 1) \\
&\quad \times \int \var{W' | y'} \cdot \exp \left( \frac{\beta - 1}{\beta \sigma_c} u + \nu'_1 \right) f(s' | y) ds', \\
\frac{\partial \Pi(y | \omega)}{\partial \theta} &= -\epsilon^2 - \delta(\beta - 1) \int (\epsilon')^2 \cdot \exp \left( \frac{\beta - 1}{\beta \sigma_c} u + \nu'_1 \right) f(s' | y) ds', \\
\frac{\partial \Pi(y | \omega)}{\partial \rho} &= \delta(\beta - 1) \int \exp \left( \frac{\beta - 1}{\beta \sigma_c} u + \nu'_1 \right) f(s' | y) ds', \\
\frac{\partial \Pi(y | \omega)}{\partial \sigma_c} &= \frac{1}{\sigma_c} \int \left\{ \Lambda(s' | \mu, \beta) - \left[ (\beta - 1)u' + \nu'_1 \right] \cdot \exp \left( \frac{\beta - 1}{\beta \sigma_c} u' + \nu'_1 \right) \right. \\
&\quad \left. + \left[ (\beta - 1)u + \nu'_1 \right] \cdot \exp \left( \frac{\beta - 1}{\beta \sigma_c} u + \nu'_1 \right) \right\} f(s' | y) ds', \\
\frac{\partial \Pi(y | \omega)}{\partial \beta} &= (\beta - 1) \int \Lambda(s' | \mu, \beta) f(s' | y) ds', \\
\frac{\partial \Pi(y | \omega)}{\partial \mu} &= \frac{1}{\beta} \int \left\{ \Lambda(s' | \mu, \beta) \left[ (\nu'_1 - u') \cdot \exp \left( \frac{\beta - 1}{\beta \sigma_c} u' + \nu'_1 \right) \right. \\
&\quad \left. + (\nu'_1 - \nu_0) \cdot \exp \left( \frac{\beta - 1}{\beta \sigma_c} u + \nu'_1 \right) \right\} f(s' | y) ds',
\end{align*}
\]

where \( u' = u(1, c', s' | \mu), \nu'_1 = u(1, c', s'), \) and \( \nu'_0 = v(0, 0, s'). \)

The following conditions are sufficient for Assumption 3:

1. For any \( y \) and \( y' \) in \( Y \), there is a first-order stochastic dominance relationship between \( f(s' | y) \) and \( f(s' | y') \).

2. \( \var{W | y} \) is weakly monotone in \( s \) on \( Y \) but is not a constant function.

3. \( e^2 \) and \( \var{W | d, c, s} \) are linearly independent on \( Y \).

4. \( \Lambda(s | \mu, \beta) \) is strictly increasing in \( s \) on \( Y \)

These conditions are readily satisfied in the study’s empirical setting: condition 1 holds when \( y \) affects only the mean of \( s' \), conditions 2 and 3 are implied by the nonlinear structure of the compensation scheme, and condition 4 follows from the extreme value distribution assumption.

If \( f(s' | y) \) first-order stochastically dominates \( f(s' | y') \), we have that \( \int a(s') f(s' | y) ds' \geq \int a(s') f(s' | y) ds' \) for any weakly increasing function \( a \). Thus, conditions 1–4 jointly imply that the expected future payoffs vary across \( y \) and that the derivatives with respect to \( \sigma_c \) and \( \beta \) are linearly independent. The derivatives with respect to \( \gamma, \theta, \) and \( \beta \) are linearly independent by condition 3. By condition 4, the derivative with respect to \( \delta \) is linearly independent of the other derivatives.

**A.5. Proof of Theorem 1**

Let \( \omega = (\mu, \delta, \beta) \) denote the vector of parameters, and suppose that \( \omega_0 \) is the true value of these parameters. The vector of true parameters \( \omega_0 \) is said to be locally identified if there exists a positive number \( \zeta \) such that no other parameter value \( \tilde{\omega} \neq \omega_0 \) satisfies \( \Pi(\tilde{\omega}) = 0 \) and \( ||\tilde{\omega} - \omega_0|| < \zeta \). That is, \( \omega_0 \) is the unique solution to \( \Pi \) within a certain radius.

The true parameter \( \omega_0 \) solves \( \Pi(y | \omega_0) = 0 \) for all \( y \). Although \( y \) has infinite support, the information necessary for identification is up to the number of the parameters. Let \( \{y_1, y_2, ..., y_l\} \) be a subset of the support of \( y \) satisfying Assumption 3. Denote the equations evaluated at the subset by

\[
\pi(\omega) = \begin{pmatrix} \Pi(y_1 | \omega) \\ \vdots \\ \Pi(y_l | \omega) \end{pmatrix},
\]

and let \( \pi' \) denote the derivative of \( \pi \) with respect to \( \omega \), evaluated at \( \omega_0 \). A sufficient condition for local identification of \( \omega_0 \) is \( \text{rank}(\pi') = \dim(\omega) \) (Chen et al. 2014), which directly follows from Assumption 3. □

**Endnotes**

1. Empirical studies that examine unobserved choice variables in a dynamic setting include Misra and Nair (2011) and Chung et al. (2014), which analyze sales force behavior with effort unobserved, and Cosguner et al. (2018), which estimates a dynamic oligopoly pricing model in which retail prices are observed but wholesale prices are not.

2. As of 2018, only Brazil, New Zealand, and the United States allow direct-to-consumer advertising with varying restrictions on mode and content.

3. To focus on salespeople’s behavior toward selection (voluntary turnover), we treat layoffs as a separate strategic decision by the firm and do not consider involuntary departures. The involuntary turnover rate of the firm was 7% in 2017; the majority of those laid off were salespeople in their probation period (less than one year since hire).
Because the firm chose participants in the primary training sessions based on an entire division or seniority, there exists unique variation in training hours that is exogenous to individual performance. In addition, the salespeople who joined the firm during the observation period add to this variation because they missed the training opportunities in the earlier periods.

All monetary figures in this study are in U.S. dollars, converted using the exchange rate at the beginning of the data period (January 2015).

As shown in Table 3, salespeople receive a small fraction of the bonus when sales are at 90%–99% of the quota, starting from the second quarter. Hence, in strict terms, “to meet the quota” would mean that sales are at or above 90% of the quota. However, the firm avoids using this definition to discourage underachievers from believing that they are performing adequately. This study follows the firm’s terminology, indicating that a salesperson meets the quota when sales are at or above 100% of the quota.

The period in the empirical application is a month.

No agent in the data returned after departing from the firm.

As is standard in the literature, the error term satisfies the conditional independence assumption (Rust 1987) in that, in a given period, it is not a function of an agent’s effort allocation decision ($e_i$). That is, the error term (unobserved state) realizes ex ante of the agent’s current-period effort decision.

An agent can obtain positive sales performance with no effort under various contexts, including customers’ (a) need-based purchases without any salesperson interaction and (b) repeat purchases based on previously built relationships.

Strictly speaking, individual heterogeneity can also be interpreted as the baseline level of effort. Because we cannot directly observe effort, the two effects (baseline ability and baseline effort) are not distinguishable from each other. Thus, effort $e_i$ represents the agent’s additional contribution to performance from the baseline.

More formally, the agent has a rational expectation on the law of motion: the agent knows the distribution of the performance shock $\xi_t$, which affects the transition probability of future states.

The mean-variance utility represents a second-order approximation to a general concave utility function with constant absolute risk aversion.

Although illustrated based on the institutional setting, our model is applicable to a wide class of nonlinear compensation systems.

The firm’s compensation scheme shown is for 2017 (i.e., during periods $t = 25, \ldots, 36$). There were some variations in the compensation scheme for 2015 and 2016.

For brevity, we suppress the optimality notation ($) throughout the study.

Note that once the agent leaves the firm ($d_i = 0$), the absorbing state implies that (a) effort $e_i = 0$ in all subsequent periods, and (b) the recursive formulation in Equation (4) degenerates to receiving the reservation value $p_i$ in perpetuity.

Note that the agent’s state variables $s_t$ are computed given the agent’s performance history $q_t$ and the firm’s compensation scheme $PS_t$.

Conceptually, obtaining the solution to this problem is equivalent to finding an inverse mapping of the nonlinear integral. Even if there exists a unique solution, it is known to be extremely difficult, if not impossible, to obtain.

The BIC values for one- and two-segment quasi-hyperbolic discounting models are 11,793.79 and 11,169.31, respectively.

Although depicted in a single plot for visual illustration, the respective segments in the exponential and quasi-hyperbolic models are not directly comparable because the segment members—despite being similar—are not fully identical given that they are from different model specifications.

In addition, tenure is within the focal firm, which may lead to underestimating its effect on the outside option (compared with industry tenure).

Table 2 provides the data to derive this figure: $2,400 \approx (1,513.58 \times 12 + 5,611.07) \times 10%$.

Providing 19.5 hours of training costs $37 \times 19.5 = 721.5; 4\%$ of annual salary is $1,500 \times 12 \times 4\% = 720.$

The performance figures tend to be lower than the segment characteristics in Table 6 because the respective new hires have zero tenure and no training.

This counterfactual exercise can also be viewed as the impact of not targeting any particular type of salespeople during the recruitment process. We thank the associate editor for providing this intuition.

Whether to recruit experienced versus rookie salespeople was one of the main concerns for the firm.

To compute the segment probabilities conditional on tenure, we apply Bayes’ theorem. For example, the probability of an experienced salesperson belonging in segment 3 given by $Pr(\text{Segment 3} | \text{Midlevel}) = Pr(\text{Midlevel} | \text{Segment 3}) \cdot Pr(\text{Segment 3})/Pr(\text{Midlevel}) = 0.284 \cdot 0.226/0.244 = 0.263$. An implicit assumption is that the tenure within the focal firm reflects the sales force characteristics at the industry level.

The individual-specific fixed effect $a_i$ is identified (and, thus, consistently estimated) in the case of a large $T$ (i.e., $T \to \infty$). In the empirical analysis, the fixed-effects parameters are estimated at the aggregate level (rather than at the individual level) using panel data with fixed $T$.

The proof builds on that of lemma 1 in Magcan and Thesmar (2002).

The proof uses a similar argument as in the proofs for corollary 3 and proposition 4 in Magcan and Thesmar (2002).

The local identification approach is the standard definition of identification in the economics literature (e.g., Chen et al. 2014). Global identification can be achieved by assuming that the second derivative is globally convex or concave.

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