V. KUMAR, SARANG SUNDER, and ROBERT P. LEONE*

Research on sales force evaluation has mostly relied on reflective metrics such as sales volume, revenue, and manager evaluations to assess and manage a sales force. However, businesses are moving from a product-centric to a customer-centric view and from a backward-looking to a forward-looking strategic perspective, so sales organizations must adapt to the ever-changing marketplace to maximize performance. The authors propose a forward-looking and profit-oriented metric to evaluate and demonstrate the effects of training type and incentive type on a salesperson's future value. Using a latent class modeling approach, they identify two distinct segments in the sales force that exhibit different responses to varying levels of training and incentives. This suggests that a one-size-fits-all approach to sales force management may be suboptimal. Finally, the authors also evaluate the magnitude of the proposed effects in the short run as well as the long run and show that the magnitudes of the effects could vary depending on the time horizon being considered. The authors close with a discussion of the implications for research and practice, including sales force evaluation through customer relationship management–based heuristics and optimal training and incentive management.

Keywords: salesperson performance evaluation, incentive management, training management, salesperson future value, customer lifetime value

Measuring and Managing a Salesperson's Future Value to the Firm

The sales force is one of the most important cogs in the business-to-business (B2B) selling process because, for most companies, it is the salesperson who initiates, develops, and nurtures the customer relationship. Given the dynamic and extremely competitive nature of the marketplace, it is critical for companies to manage their sales forces proactively to maximize customer loyalty and firm value as well as minimize risk (Palmatier, Scheer, and Steenkamp 2007). Firms currently operate in a highly volatile dynamic environment in which the strength of the customer relationship governs the firm's bottom line. The importance of the customer relationship is further underscored in the B2B context because the products and services being transacted are, in general, more complex and involve a greater amount of selling effort on the firm's part. Prior research has emphasized the importance of retaining key salespeople because they are the custodians of the firm's relationship with the customer and are often relied on when gathering competitive intelligence in the marketplace (Bendapudi and Leone 2002; Hughes, Bon, and Rapp 2013; Rapp, Agnihotri, and Baker 2011). Although some researchers have investigated what makes a good salesperson, in terms of individual characteristics and/or firm factors (Ahearne et al. 2010; Jones et al. 2007), to date, no research has investigated the salesperson's future value

*V. Kumar (VK) is the Chang Jiang Scholar (HUST), Richard and Susan Lenny Distinguished Chair & Professor of Marketing, and Executive Director (e-mail: vk@gsu.edu), and Sarang Sunder is a doctoral student in Marketing (e-mail: ssunder1@gsu.edu), Center for Excellence in Brand and Customer Management, J. Mack Robinson College of Business, Georgia State University. Robert P. Leone is the J. Vaughn and Evelyne H. Wilson Chair and Professor of Marketing, Neeley School of Business, Texas Christian University (e-mail: r.leone@tcu.edu). The authors thank the firm for providing access to proprietary data. They are grateful to the participants of the 2012 Thought Leadership on the Sales Profession conference at Harvard Business School as well as to Gayatri Shukla, Adam Rapp, and Andrew Petersen for their valuable insights and suggestions. The authors thank three anonymous *JMR* reviewers for their valuable comments on a previous version of this article. Finally, the authors are grateful to Renu for copyediting a previous version of the manuscript. Rajdeep Grewal served as associate editor for this article.

ISSN: 0022-2437 (print), 1547-7193 (electronic)

(SFV) to the firm and how organizational factors (opt-in training and incentives) can affect that value. From a cost perspective, managing the sales force is an expensive proposition in itself. Zoltners, Sinha, and Lorimer (2008) report that the U.S. economy spends $800 billion on sales forces every year, which is approximately three times the average advertising spend in the same period. Therefore, in addition to helping firms determine SFV, it is our objective to help them manage their expenditure levels (training and incentive investments) to maximize that future value. Specifically, in this study, we attempt to answer the following research questions: (1) How should the future profit potential of the salesperson be measured? (2) What are the drivers of a salesperson's future performance, and what is their impact? and (3) Is there significant heterogeneity within the sales force that affects future performance? Using the empirical application described in this study, we are able not only to measure the effects but also to determine whether the effects are consistent in the short run (one-year future window) as well as the long run (three-year future window).

We propose a metric to value the salesperson on the basis of the future profit potential (measured through the customer lifetime value [CLV]) of his or her customers. Research has shown that this approach of valuation from the customer's perspective yields benefits to the firm (in terms of, e.g., profits, operational efficiency, sales, market capitalization; see, e.g., Kumar and Shah 2009). In addition to evaluating the future potential of the salesperson, we attempt to uncover the drivers of SFV (in the short run and the long run) and provide managerial recommendations. Using extant theories of motivation and ability, we develop a conceptual framework to explain the creation of SFV through opt-in training interventions and incentives management. Following Cron et al.'s (2005) theoretical conceptualization, we also show how different types of training interventions affect SFV. Specifically, in the empirical application presented herein, we study the impact of opt-in training interventions directed toward improving the salesperson's task-related and growth-related knowledge, skills, and abilities. In addition, we quantify the impact of monetary and nonmonetary forms of incentives that are commonly used in the marketplace to encourage the salesperson to perform better. We test our hypotheses using data from three sources (customer level, salesperson level, and firm level) from a *Fortune* 500 B2B firm. We estimate the proposed model while accounting for unobserved heterogeneity (through latent class segmentation) and endogeneity (using instrumental variables). The data we use in this study enable us to investigate whether the results we observe hold in the short run (one year) as well as the long run (three years) or whether the time horizon of interest produces different findings. Our analysis, which accounts for the length of the time frame under consideration, would be beneficial for sales managers tasked with maximizing profit from an individual salesperson within a specific time frame.

This article is structured as follows. We begin by discussing the research gap and its significance. Next, we introduce the SFV concept as an improvement over extant measures of salesperson performance. We then discuss the hypothesized drivers of SFV, elaborate on the rationale behind each link in the conceptual framework, and present the hypotheses tested in the article. Next, we discuss the methodology (model development and estimation) used to test the proposed hypotheses. In the final section of the article, we discuss model results and the managerial implications of adopting an SFV-based system and suggest avenues for further research.

RESEARCH MOTIVATION

Owing to the significant investments made in training and the influence of a salesperson's performance on a company's profitability, it is imperative that managers have the ability not only to measure a salesperson's current performance but also to predict the salesperson's performance into the future. The lack of this capability could lead to myopic and ill-advised sales force management. Furthermore, because marketing thought is shifting from a product-centric to a customer-centric view, it is imperative that sales organizations adapt accordingly by viewing their sales force from a customer profitability standpoint and be able to forecast sales force profit potential. The importance of having a suitable metric for salesperson evaluation is further evident when managing salesperson churn, which is considered a major pain point for firms, especially in the B2B space, in which the selling process is more complex and customer loyalty is heavily in the control of the salesperson (Palmatier, Scheer, and Steenkamp 2007). Bendapudi and Leone (2002) show that there is a good possibility that churning salespeople could take valuable customers with them. It is therefore extremely important for the sales manager to know which salespeople are more valuable (in terms of future profits), whom to focus on retaining, and whom to let go. Given the current economic climate, the importance of retention has never been greater as companies are aiming to "shed some weight."

Performance evaluation metrics in the sales force literature can be categorized into (1) evaluations by knowledgeable others, (2) self-evaluations, and (3) quantitative measures (Behrman and Perreault 1982). Evaluations by knowledgeable others (e.g., peer evaluations, manager evaluations) and self-evaluation metrics tend to suffer from respondent subjectivity biases and have been shown to have low convergent validity (Jaramillo, Carillat, and Locander 2005). Quantitative measures, in contrast, are objective measures of performance (e.g., revenue generated, unit sales, conversion rates). Although they are easy to implement in the marketplace, quantitative metrics tend to reward salespeople's past behavior while ignoring future profit potential. To account for future potential within the performance metric, managers need to adopt a model-based approach to evaluating the salesperson. Given the increasing acceptance of customer relationship management (CRM)–based valuation methods in management practice (Tanner et al. 2005), another important criterion that must be satisfied is that the salesperson evaluation metric must be built up from customer-level profitability measures (e.g., CLV). In this study, we contribute to sales force performance evaluation research by proposing a forward-looking, profit-oriented metric derived from CRM concepts to measure and predict the future value of a salesperson. In addition, we present an empirical implementation of the SFV concept and quantify the effects of training and incentives on a salesperson's future value to the firm.

MEASURING SFV

We define a SFV as the net present value (NPV) of future cash flows from the salesperson's customers after accounting for appropriate costs associated with the salesperson. In general, the SFV metric can be computed as follows:

(1a) $SFV_j = (\text{NPV of Future } CM_j - \text{NPV of Relevant } Costs_j)$.

We measure the future contribution margin associated with a salesperson j in terms of the total CLV (i.e., customer equity [CE]) from his or her existing customers as well as expected value from new customers. Because we have customer-level transaction data collected from the participating firm, we first model the lifetime profit contribution at the customer level (as CLV) and then aggregate it (across the customers the salesperson serves) for each salesperson to arrive at salesperson-level CE. We use the procedure and variables Kumar et al. (2008) employ to model the CLV, the details of which are available in the "Methodology" section and the Appendix. The use of CLV (summed to arrive at CE) to measure the future cash flows for each salesperson ensures that the SFV metric is customer-centric as well as forward looking. Because we are projecting cash flows into the future, the SFV metric also must factor in the probability that the salesperson will churn by the end of the period of analysis. We compute the CE of existing customers as described previously and project the expected value (in terms of CE) earned from newly acquired customers for each salesperson. The second term in the SFV metric (Equation 1a) accounts for the costs that the firm incurs from developing and motivating the salesperson. In our implementation, we consider the NPV cost of training and incentivizing the salesperson as relevant costs. In line with this definition, the general formula to measure SFV is given as

(1b) $$SFV_j = \left[1 - P(\text{Churn})_j\right] \times \left[\left(CE_j^{\text{existing}} + CE_j^{\text{new}}\right) - \text{NPV of Relevant Costs}_j\right].$$

In the field study presented herein, however, we do not observe salesperson churn within the time window; thus, $P(\text{Churn})_j = 0$ in this case.[1] Therefore, for the application described in this study, we compute SFV as shown in Equation 1c. Note that Equation 1c can be estimated for various time windows depending on the time horizons considered by the manager and the firm. In the current implementation, we compute and draw conclusions for SFV calculated in the short run (one year in the future) and long run (three years in the future). This enables us to provide managers with guidance on the effects of training interventions (task and growth related) and incentives (monetary and nonmonetary) on the SFV for long- and short-term managerial focus.

(1c) $$SFV_j = \left(CE_j^{\text{existing}} + CE_j^{\text{new}}\right) - \text{NPV of Relevant Costs}_j.$$

[1]We acknowledge that there could be significant salesperson churn when applying the SFV framework in the marketplace. Although we do not explicitly do so (because we do not observe churn in our sample data set), further research could build on our formulation by specifying a formal churn model to account for salesperson turnover similar to that proposed in Neslin et al. (2006). We elaborate on this in our discussion of further research.

Although we do not explicitly model $P(\text{Churn})_j$ in Equation 1c (there was no churn in our data set over the period of time investigated), we elaborate on some of the possible drivers of salesperson churn that could be investigated in further research. Williamson (1983) outlines the main causes of salesperson turnover as (1) those related to low sales productivity and (2) organizational environment and company policy–related difficulties. Although it is expected that salespeople who are less productive will tend to have a higher probability of churn, the organizational factors that influence $P[\text{Churn}]_j$ are of special interest to researchers. Specifically, Brashear, Manolis, and Brooks (2005) posit that salesperson perceptions about fairness and justice of the manager influence his or her intention to leave the organization. Furthermore, they show that trust between a salesperson and his or her manager governs the relationship between justice and turnover intention. In their meta-analysis, Hom et al. (1992) corroborate the results from turnover theory (Mobley, Horner, and Hollingsworth 1978) and show that employee turnover is heavily influenced by job satisfaction and the availability of alternatives. To specify a model to predict salesperson churn, we turn to extant CRM research on customer churn. The probability of churn for salesperson j can be specified as a function of j's own characteristics (e.g., demographics, tenure with the firm), job perceptions (e.g., satisfaction with pay, peers, organizational role), and organizational factors (e.g., supervisor fairness/justice, trust, supervisory control), in line with prior research on employee turnover (Brashear, Manolis, and Brooks 2005; Hom et al. 1992; Sager, Varadarajan, and Futrell 1988). In Equation 1d, $f(\cdot)_j$ represents the functional form that can be used to model $P(\text{Churn})_j$. The functional form chosen for modeling churn could be logistic regression, decision trees (Neslin et al. 2006), or survival/hazard models (Gupta et al. 2006).

(1d) $$P(\text{Churn})_j = f(\text{own characteristics, job perceptions, organizational factors})_j.$$

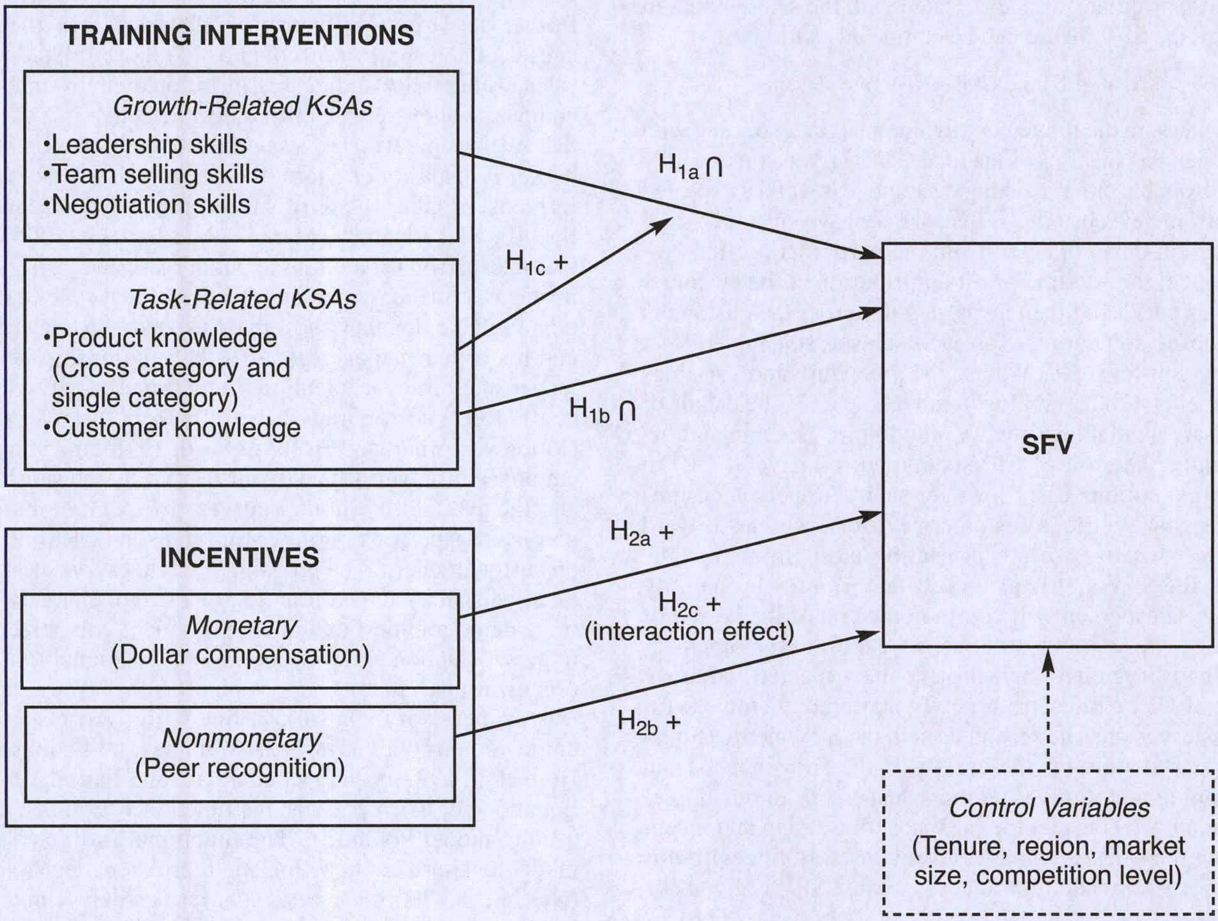
MANAGING SFV

Figure 1 describes the conceptual framework and the hypothesized drivers of SFV. Relying heavily on expectancy theory (Walker, Churchill, and Ford 1977) and the knowledge, skills, abilities, and other characteristics framework (Kanfer and Ackerman 2005), we attempt to uncover the underlying mechanisms of salesperson performance (measured as SFV) and describe the impact of organizational drivers such as opt-in training and incentive management on SFV. In this section, we describe the relationship between training interventions and a salesperson's future performance (measured as SFV) using the knowledge, skills, abilities, and other characteristics framework. Then, we describe the relationship between incentives (both monetary and nonmonetary) and SFV using extant research on incentive management in the sales context.

Linking Training Interventions and SFV

From a cost perspective, it is critical for firms to adopt an aggressive and proactive sales training strategy. The American Society for Training and Development estimates that U.S. businesses spend $15 billion every year on sales train-

Figure 1
DRIVERS OF SFV



ing, which amounts to approximately $2,000 per salesperson (Salopek 2009). Most training and development programs currently undertaken at firms are geared toward increasing the salesperson's knowledge, skills, and abilities (KSAs) that are considered relevant for selling effectiveness. Trained KSAs are malleable characteristics (e.g., declarative knowledge, procedural knowledge) that are open to change and enhancements through various training interventions. To maximize the KSAs gathered by the salesperson, firms incorporate specific training interventions to increase the salesperson's task-related and growth-related KSAs (Cron et al. 2005). The evaluation of sales training is often difficult because of practical and methodological barriers. Attia, Honeycutt, and Attia (2002) outline four main difficulties that managers face when evaluating training in the sales domain: (1) managerial perceptions, (2) evaluation restrictions, (3) methodological problems, and (4) lack of empirical evidence. These challenges are further exacerbated in the marketplace because not all salespeople receive the same type and level of training. The decision of whether the salesperson receives a specific kind of training is made either by the manager (through training allocations) or the salesperson (through opt-in training sessions). In this study, we focus on the effect of opt-in training interventions (beyond the basic training that every salesperson is mandated to undergo) on the future performance of a salesperson. We address some of these difficulties by investigating not only the impact of opt-in training interventions but also the differential impact of the training content (task-related and growth-related KSAs) on SFV. Specifically, we develop hypotheses to study the impact of specific opt-in training interventions on SFV in the short run and the long run. In this section, we develop hypotheses to explain the effect of two types of common training interventions (task related and growth related) on the SFV.

Task-related training and SFV. A majority of training efforts that firms undertake focus on improving KSAs that would directly assist in the selling function. Task-related KSAs pertain to essential elements that a salesperson must possess to begin selling the company's offerings (Cron et al. 2005). Most training programs instituted by the firm fall within task-related training interventions because they are directly relevant to the selling function and its effectiveness. From a knowledge perspective, these interventions include information about the products/services, industry factors and compliance, consumers, and related areas. The focus of task-related training is to assist the salesperson in accessing and using knowledge resources that would improve sales productivity. To sell effectively, the salesperson also must possess skills that enable efficient management of time, customers, and selling effort. Furthermore, as the marketplace becomes more customer-centric, salespeople's roles are shifting from product selling to managing customer relationships, which requires people and selling skills. In response to the aforementioned paradigm shift, task-related training programs are also geared toward improving the salesperson's selling and relationship-building skills (Weitz, Sujan, and Sujan 1986). Although we expect training to have a positive impact on the salesperson's performance (Dubinsky 1981; Roman, Ruiz, and Munuera 2002), this relationship does not need to be linear. Caldieraro and Coughlan (2002) develop an analytical model to describe the relationship between training and salesperson performance at the individual level. They argue that each unit of training produces a positive but diminishing effect on salesperson performance. As Wilson, Strutton, and Farris (2002) note, the effectiveness of a training intervention is heavily dependent on the transfer of learning in the marketplace. Especially in a dynamically changing marketplace, salespeople who have been "overtrained" have less exposure and less chance to apply their learning on the job and calibrate their selling skills to evolving product offerings and customer needs. Financially speaking, training salespeople represents a cost for the firm that must be accounted for when computing SFV. Thus, an overtrained salesperson leads to a higher cost structure than does an optimally trained one. There exists an optimal level of training that can be provided to each salesperson to maximize its effect on his or her performance (Krishnamoorthy, Misra, and Prasad 2005). Therefore, from cost and training effectiveness standpoints, we expect that as the level of task-related training reaches a saturation point for the salesperson, its positive impact on his or her SFV will begin to diminish as training hours increase.

H_{1a}: The effect of task-related training has an inverted U-shaped relationship with SFV.

Growth-related training and SFV. Although knowledge gained through task-related training is a good starting point, such training provides only restrictive development of the salesperson's KSA. As the complexity of the selling situation/environment increases, salespeople are required to implement quick problem-solving heuristics to sell effectively (Mintu-Wimsatt and Gassenheimer 2004). To ensure salespeople's continual growth, firms provide specific training aimed to increase growth-related KSAs (i.e., those that a salesperson requires to enable the growth and development of his or her repertoire of task-related KSAs; Cron et al. 2005). Unlike task-related training, growth-related training programs focus not only on effecting a behavioral change in the salesperson but also on modifying his or her attitudes toward respective tasks or goals. That is, such programs increase the salesperson's global tacit knowledge and eventually lead to an adaptive behavior. Training interventions for these types of KSAs include "if/then" rules of thumb (Weitz, Sujan, and Sujan 1986), customer decision-making processes (Weitz 1978), and coping styles and strategies (Nonis and Sager 2003). Similar to task-related training, we expect that the effect of growth-related training, though positive, diminishes as the training hours increase because the cost structure of training begins to dominate the SFV.

H_{1b}: The effect of growth-related training has an inverted U-shaped relationship with SFV.

As we noted previously, growth-related KSAs can help the salesperson develop "learning to learn" KSAs such as adaptability and complex problem solving. In addition to its direct influence on SFV, growth-related training also enhances the impact of task-related training. Growth-related KSAs help the salesperson accurately pinpoint the task-related KSAs required to increase sales performance. For example, adaptive ability (developed through growth-related training) enables a salesperson to modify his or her direct selling behaviors (developed through task-related training) to accommodate customers' needs and wants. Especially in complex selling situations, salespeople use their growth-related KSAs to tailor their selling tactics to each customer as well as to make rapid adjustments on the basis of the customer's response. Indeed, McFarland, Challagalla, and Shervani (2006) show that the complexity of selling is high, and it is necessary for salespeople to recognize this complexity and adapt their behavior (influence tactics) accordingly. However, salespeople not trained in growth-related KSAs (e.g., adaptability) may have difficulty modifying their tactics (task-related KSAs) quickly enough to sell effectively. Growth-related training helps the salesperson learn more (during task-related training), and thus, we hypothesize that growth-related training moderates the relationship between task-related training and SFV. Formally,

H_{1c}: As growth-related training increases, the nonlinear relationship between task-related training and SFV is strengthened.

Linking Incentives to SFV

Motivating salespeople is one of the most important objectives of the sales manager. Expectancy theory predicts that extrinsic motivation positively influences performance (Oliver 1974). Extrinsic motivation is mainly decomposed into two empirically and theoretically distinct components: compensation seeking and recognition seeking (Miao, Evans, and Shaoming 2007). Firms use various incentive mechanisms to improve and motivate salespeople to expend more effort and eventually perform better. Specifically, compensation-seeking behavior is influenced by monetary incentives (dollar compensations), whereas recognition-seeking behavior is induced by nonmonetary incentives (peer recognition and other awards). Each of these incentives affects salespeople's future performance to a different extent. In this study, we attempt to quantify these effects in an empirical setting.

Monetary incentives and SFV. Firms adopt many kinds of compensation systems to increase salesperson productivity. Churchill, Ford, and Walker (1997) separate these systems into three categories: straight salary plans, straight compensation plans, and combination plans. We develop hypotheses for the straight compensation system because it is most commonly used among sales organizations in the high-tech B2B industry because of its practical applicability. The other advantage of such a system is that it yields immediate results, which enable the sales managers to evaluate the impact of the incentive easily. We define a monetary incentive as the added compensation in dollars (in addition to the base salary levels) the salesperson receives for every sale he or she makes above the stipulated goal set by the firm. Firms' use of "merit pay" has been the focus of human resource management research for some time, whereby the manager is instructed to explicitly demonstrate the link between performance/motivation and rewards (Segalla et al. 2006). Theories involving human motivation support the use of incentives to motivate people to perform better. Researchers have primarily relied on expectancy theory to explain the impact of compensation on salesperson performance. Expectancy theory suggests that financial incentives increase a person's tendency to expend more effort toward the task and, consequently, increase performance. Although this is true, sales force motivation can also be viewed as a cycle: selling effort increases performance, which generates rewards (compensation) and finally motivates the salesperson to increase selling effort (Coughlan and Narasimhan 1992; Ford, Churchill, and Walker 1985), thereby leading to improved performance in the future.

H_{2a}: The level of monetary incentives a salesperson receives positively influences his or her future value.

Nonmonetary incentives and SFV. Not everyone is motivated by monetary rewards. To account for this possibility, firms incorporate nonmonetary incentives (e.g., peer recognition, awards) into their sales force control systems to motivate salespeople to perform better. The use of such incentives makes the salesperson more aware of how well she is performing relative to her peers and motivates her to work harder to keep herself ahead of her peers (Kohli, Shervani, and Challagalla 1998). Indeed, when there is a high congruence between the salesperson's values and the values ascribed by the organization, research has shown that social recognition and nonmonetary reward systems perform better (Apasu 1987). From a theory perspective, social reinforcement theory predicts that higher motivation among individuals could arise from the social utility (from peers, friends, and family) of achieving the goal (Stajkovic and Luthans 1997). We use "peer recognition" as a proxy for nonmonetary incentives used by the focal firm. We thus expect that nonmonetary incentives such as peer reviews or awards (e.g., "Salesperson of the Month") can be used to motivate the salesperson to expend more effort and eventually perform better. Following this rationale, we hypothesize the following:

H_{2b}: The effect of nonmonetary incentive level on SFV is positive.

In addition to the main effects, we also expect a synergistic effect of monetary and nonmonetary incentives on SFV. Salespeople who receive monetary as well as nonmonetary incentives are likely to be more motivated than salespeople who receive only one type of incentive. To test this theory, we hypothesize that the interaction of monetary and nonmonetary incentive levels will also have a positive influence on SFV. Formally stated,

H_{2c}: The effect of the interaction between nonmonetary and monetary incentive levels positively influences SFV.

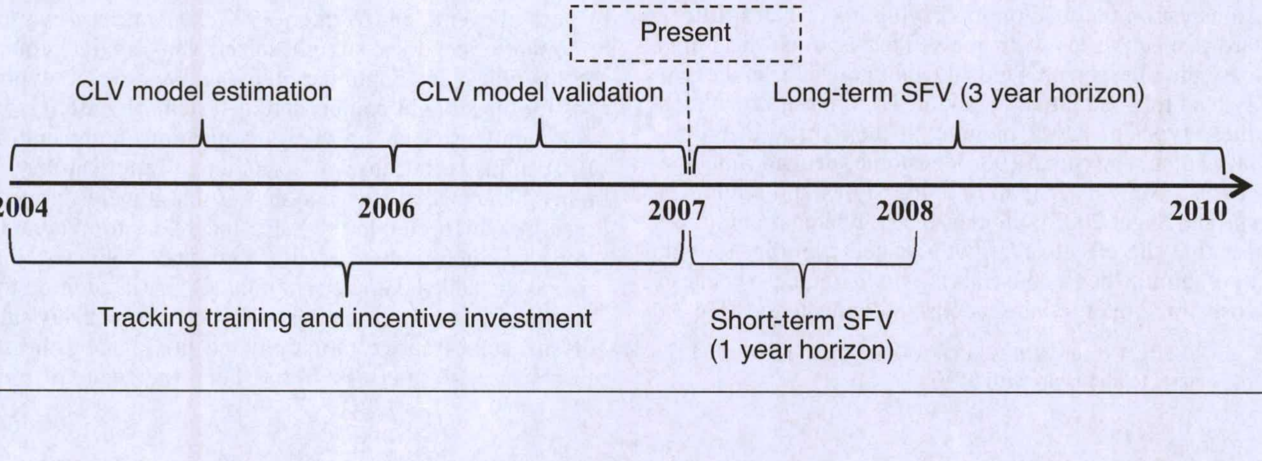
In the following section, we explain how we apply our conceptual framework (Figure 1) to a *Fortune* 500 B2B firm as a means of testing the hypotheses. Subsequently, we discuss the methodology used in the study, with specific details regarding model specification and estimation and addressing endogeneity and heterogeneity issues.

DATA DESCRIPTION AND MEASURES

The data come from a *Fortune* 500 firm that sells high-tech software, hardware, and services in the B2B space. The focal firm provided us with information on 484 salespeople over a period of seven years (2004–2010). The product portfolio for the salespeople in the sample was similar, which would help rule out any demand effects that arise from the type of product or service being sold. To test our hypotheses, we need data from three sources: (1) transactional data from the customer, (2) attitudinal and reported data from the salesperson, and (3) organizational factors (training and incentive data). We test the proposed hypotheses using a field study conducted in collaboration with the B2B firm. The main objective of the collaborating firm was to identify the impact and effectiveness of training intervention type and incentive type on the future value of the salesperson. Figure 2 describes the timeline of the field study.

In the field study, the firm instituted organizational factors (opt-in training interventions and incentive investments) during the first three-year period (January 2004–December 2007). Salespeople opted in to training interventions (task related or growth related) throughout this period. Similarly, the monetary and nonmonetary reward systems were also recorded for each salesperson during the study period. Although the salespeople still received incentives during the period January 2007–December 2010, there were no changes

Figure 2
STUDY TIMELINE



to the compensation structure or the reward criteria. We account for these expenses in the SFV computation (Equation 1c).

Computing SFV

As we describe in Equation 1c, computing SFV involves computing the aggregated CLV (of the customers served by the salesperson) for each salesperson and subtracting the relevant future expenses incurred by the firm. Before projecting the salesperson's profit potential into the future, we must calibrate the CLV model for accuracy. To do so, we first estimate a CLV model using the customer-level transaction data (including gross contribution margins, marketing costs, and retention information) from January 2004 to December 2006 and predict the CLV for the following year (January 2007–January 2008). We compute the CLV following Kumar et al. (2008); estimation details and procedure are available in the Appendix. To gauge the accuracy of the CLV model, we use the mean absolute percentage error (MAPE), a commonly used error measure in forecasting (Armstrong and Collopy 1992).[2] The MAPE is a preferred metric to gauge predictive accuracy because it is unit free and is easier to interpret. In the current implementation, our CLV model performs satisfactorily (MAPE = 9.8%). A MAPE of 9.8% shows that our model predicts the customer's profitability in the following year with an accuracy of 90.2%. Given that the proposed CLV model performs well, we then reestimate the model using transaction data from January 2004 to December 2007 to predict CLV for the upcoming one-year (2008) and three-year windows (2008, 2009, and 2010). We measured the corresponding model performance for the one-year profit window (from January 2008 to December 2008) and the CLV (three-year horizon from January 2008 to December 2010) using MAPE and found it to be 9.4% and 15.1%, respectively. The sum of the CLVs for each salesperson represents the first term in Equation 1c. The focal firm allocates salespeople to clients such that all salespeople are presented with the same selling opportunities within the operating region. The heuristic for territory allocation is based on the aforementioned CLV model (among the current customers) and the firm's proprietary model for pipeline opportunities (for prospects) for the salesperson.

To compute the second term in Equation 1c, we add the relevant expenses that the firm incurs and apply the discount rate to arrive at the NPV of all relevant expenses incurred on the salesperson.[3] Then we can easily subtract the second term from the first and arrive at the SFV score for each salesperson. In this study, we compute short-term SFV using the one-year horizon (2008) and compute long-term SFV using the three-year horizon (2008–2010). We chose a three-year horizon to project a salesperson's long-term future value for three reasons. First, from our interactions with the focal firm, we learned that managerial decision-making horizons were always limited to a three-year future window because the business environment (B2B high technology) would remain stable for only three years. Second, from a forecasting point of view, we find that the predictive accuracy of the CLV model deteriorates considerably as we attempt to predict customer behavior beyond a three-year horizon at any given time. These inaccuracies are further inflated when we aggregate the CLV at the salesperson level to arrive at SFV. Third, in most cases, the majority of a customer's lifetime value is captured within the first three years (because discounting decreases the contribution of profits after that point). Thus, most CLV applications are based on CLV estimates over a rolling three-year window (Gupta and Lehmann 2005; Kumar et al. 2008).

Measuring Training and Incentives

Training interventions. With regard to the training interventions, all salespeople in the sample underwent a basic level of mandatory training to improve salesperson KSAs. In addition, they were allowed to opt in to training interventions (task related or growth related) during the study period of 2004–2010. Similar to Roman, Ruiz, and Munuera (2002) and Ahearne, Jelinek, and Rapp (2005), we quantify the amount of training interventions that the salesperson has undergone by measuring the number of hours of training activity (task related or growth related) for each salesperson annually for the first four years (2004–2007) of the study period. We then use the annualized average of the number of hours of training attended for the period 2004–2007 as our measure of training (task- and growth-related training). The salespeople in the sample only underwent the mandatory training and were not given any opt-in training interventions during the remaining study period (January 2008–December 2010).

Incentives. The incentive measures used were twofold—namely, monetary and nonmonetary incentives. The focal firm archives the monetary compensation levels (in dollars) for each salesperson throughout his or her tenure with the firm. We measure monetary incentives as the average annualized commission payments (beyond the base salary) that are disbursed to the salesperson between 2004 and 2007. There were no significant changes to the incentive structures of the sales force during the remainder of the study. The focal firm uses peer recognitions such as awards and commendations as a nonmonetary incentive to motivate the sales force. We measure peer recognitions (our proxy for nonmonetary incentives) as the annualized average number of times the salesperson was recognized within the firm (through e-mail, newsletters, and awards) during the first four years of the study period (2004–2007).

Control Variables

To help alleviate the influence of extraneous factors on our analysis, we use control variables (at individual and market levels) in our model. To control for individual factors that could affect SFV, we use the tenure of the salesperson with the focal firm (in years). Furthermore, this also helps us address some of the observed heterogeneity among salespeople in the sample. To control for territorial/geographical differences among salespeople, we use dummy variables to denote the various geographical regions in which the salesperson i operates. The focal firm allocates salespeople to territories in a manner such that equal oppor-

[2]We provide the formula to compute MAPE in the Appendix.

[3]The relevant expenses used in this study are training costs and monetary incentives paid by the firm during the study period. In the current study, the only expense the firm incurred from 2007 to 2010 was monetary incentives paid to the salesperson. Furthermore, we also included the NPV of training costs incurred during 2004–2007 in the relevant expenses measure.

tunities are available to all salespeople. Although we do not hypothesize any effects for the regional dummies on our dependent variables, we expect them to influence the intercept term and therefore control for regional or geographic differences in the marketplace. In addition, we expect that industry- and market-level characteristics could affect the baseline SFV of the salesperson. Therefore, we include the market size and competition level for each geographic region in which the salesperson operates. To measure competition level for each market every year, we asked sales managers to evaluate the level of competition on a seven-point scale (7 represents the most competitive marketplace, and 1 represents the least competitive marketplace where salesperson i operated). To measure the market size every year, we used the company's projections of market size documented in its internal reports that are circulated among the sales functions in North America.

SFV in the Short Run and the Long Run

When operating in highly dynamic environments, managers need to account for the short-term as well as the long-term implications of their decisions, especially in sales force management. In this context, we expect that training interventions are likely to have a more pronounced effect on long-term performance because it takes some time for the salesperson to learn how to use the skills in the field. In contrast, we expect incentives to have a more short-term impact on salesperson performance. The richness of the available data enables us to compare and contrast the differential effects of training and incentives when considering short-term SFV (one year forward) versus long-term SFV (three years forward). Thus, we can develop implications for sales managers who have varying time orientations (short vs. long) to manage their sales force more effectively.

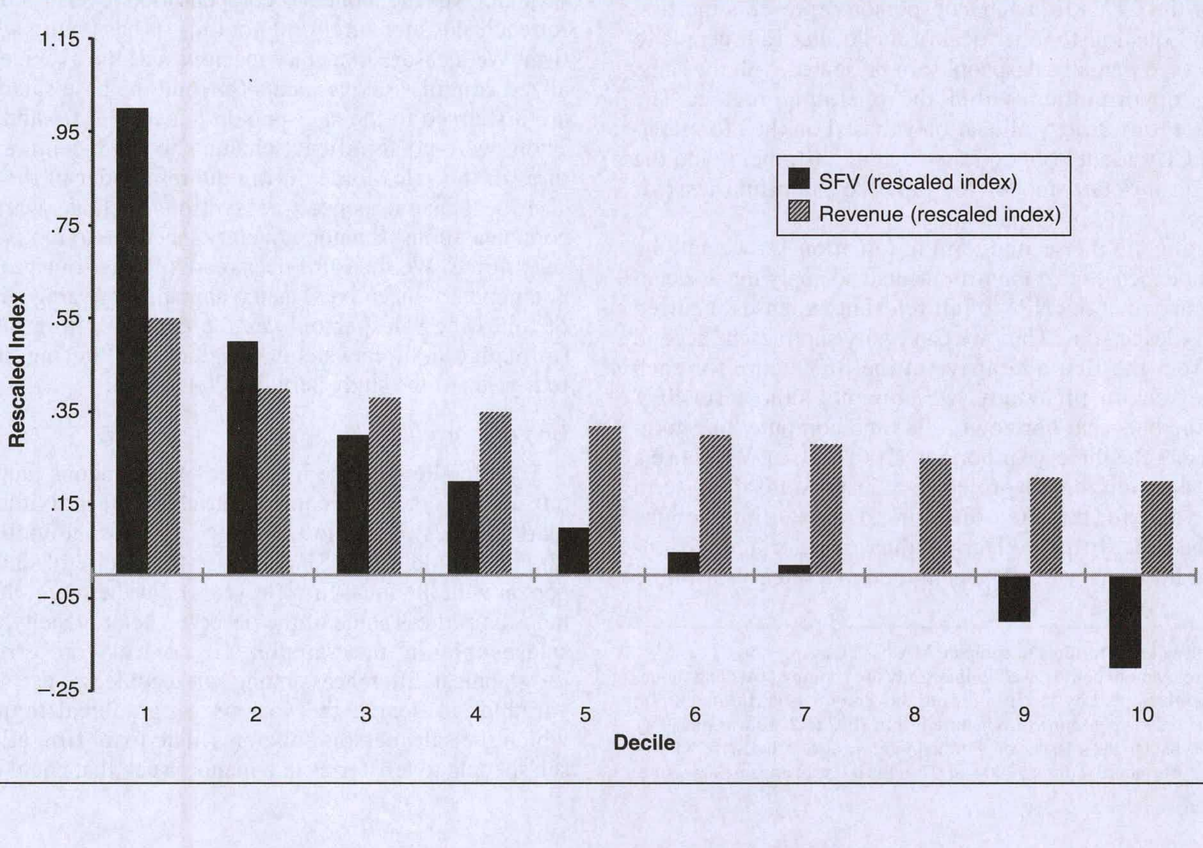
We compute short-term SFV as the profits from the clients managed by the salesperson minus the optional training costs (during 2004–2007) and any incentives paid for 2008, discounted to present value (January 1, 2008). Similarly, we compute the long-term SFV for the period 2008–2010 by computing the sum of the discounted profits (to January 1, 2008) from the clients the salesperson managed in each of the three years minus the optional training costs (during 2004–2007) and any incentives paid during each of the three-year periods, discounted to the present value (January 1, 2008). We then compute the annualized average of long-term SFV by dividing by 3. Our objective is to empirically showcase the impact of our proposed drivers (measured during 2004–2007) on (1) the short-term SFV (computed for 2008) and (2) the long-term SFV (computed as an annualized average for 2008–2010).

Figure 3 shows the distribution of the computed (long-term) SFV with the corresponding revenue generated by the salesperson. Specifically, the figure shows the distribution of the SFVs (in deciles) in decreasing order of their value. Before our study, the firm used "revenue generated" as the main metric to value its salespeople and to identify its "star" salesperson.

As Figure 3 illustrates, when determining the true value of a salesperson—in terms of customer profitability he or she brings in—current revenue generated is not a good indicator of SFV. A salesperson's performance is significantly undervalued when using current revenue generated for the

Figure 3

SALESPERSON DECILE CHART: LONG-TERM SFV (THREE-YEAR HORIZON) VERSUS REVENUE GENERATED



first few deciles and significantly overvalued for the last few. Furthermore, we find that the correlation between revenue generated and SFV is only .64, indicating that the two metrics are congruent. To check the (in)congruence of the two metrics, we compute the number of salespeople wrongly classified in Figure 3. We find that the discrepancy between the two metrics in segmenting the sales force is 27%. Thus, by using current revenue as a metric, the focal firm could be wrongly classifying a large number of its salespeople because revenue rewards prior value; in contrast, SFV also values future profit contributions. These findings further point to the need for a forward-looking metric to evaluate salespeople and provide strong evidence that current sales force management systems are not as strong as they should be. Table 1 provides the descriptive statistics of the key variables used in the model.

METHODOLOGY

We estimate a latent class model to account for the unobserved heterogeneity. We also account for the potential endogeneity problem that arises due to the opt-in nature of the training interventions using an instrumental variable approach. Next, we describe the details of the model specification and its estimation.

Model Development

To capture the hypothesized effects of training interventions and incentives on long-term and short-term SFV, we estimate two models (Equations 2 and 3). Equation 2 describes the long-term effect of training interventions (task related and growth related) and incentives (monetary and nonmonetary) on the future value of the salesperson. Specifically, we use the annualized average SFV over a three-year period (2008, 2009, and 2010) as the dependent variable in Equation 2. We hypothesize nonlinear effects of training type (task related and growth related) on SFV. To capture the hypothesized nonlinear effects, we use the square of the amount of task-related and growth-related training received by the salesperson in the equation. In addition, to test the moderating effect of growth-related training (H_{1c}), Equation 2 includes the interaction between task- and growth-related training. We hypothesize that monetary incentives and peer recognition have significant effects on SFV. We also include the interaction term between monetary incentives and peer recognition to test H_{2c}.

$$
\begin{aligned}
(2)\ \text{SFV}^{\text{long term}}_{i,\,2008\to2010} = {} & \beta_0 + \beta_1\text{Task\_Training}_{i,\,2004\to2007} \\
& + \beta_2\text{Task\_Training}^2_{i,\,2004\to2007} \\
& + \beta_3\text{Growth\_Training}_{i,\,2004\to2007} \\
& + \beta_4\text{Growth\_Training}^2_{i,\,2004\to2007} \\
& + \beta_5(\text{Task\_Training} \times \text{Growth\_Training})_{i,\,2004\to2007} \\
& + \beta_6\text{Monetary\_Inc}_{i,\,2004\to2007} \\
& + \beta_7\text{Peer\_Recog}_{i,\,2004\to2007} \\
& + \beta_8(\text{Monetary\_Inc} \times \text{Peer\_Recog})_{i,\,2004\to2007} \\
& + \psi_k\text{CTRL}_{ik,\,2008\to2010} + \varepsilon^{(\text{SFV})}_{1i},
\end{aligned}
$$

where

$\text{SFV}^{\text{long-term}}_{i,2008\to2010}$ = future value of salesperson i in the long run (2008–2010),

$\text{Growth\_Training}_{i,2004\to2007}$ = annualized average amount of growth-related training interventions (in hours) that salesperson i has undergone between 2004 and 2007,

$\text{Task\_Training}_{i,2004\to2007}$ = annualized average amount of task-related training interventions (in hours) that salesperson i has undergone between 2004 and 2007,

$\text{CTRL}_{ik,2008\to2010}$ = average computed measures of the control variables (between 2008 and 2010) as described previously,

$\text{Monetary\_Inc}_{i,2004\to2007}$ = annualized average monetary incentives received by salesperson i between 2004 and 2007,

$\text{Peer\_Recog}_{i,2004\to2007}$ = annualized average number of official recognitions received by salesperson i between 2004 and 2007,

$\beta_0 - \beta_8$, Ψ_k = parameters to be estimated, and

$\varepsilon^{(\text{SFV})}_{1i}$ = disturbance term associated with $\text{SFV}^{\text{long-term}}_{i,2008\to2010}$.

Similar to Equation 2, we estimate the impact of training and incentives on short-term SFV (measured for 2008) in

Table 1
DESCRIPTIVE STATISTICS OF KEY VARIABLES

Variable (per Salesperson)	*Measure*	*M (N = 484)*	*SD*
Short-term SFV	Annualized average over one year (in thousands of dollars)	265	101
Long-term SFV	Annualized average over three years (in thousands of dollars)	292	112
Monetary incentive[a]	Thousands of dollars	41.03	26.02
Training intervention cost[a]	Thousands of dollars	8.32	3.16
Peer recognition[ab]	Number of times the salesperson has been recognized during the study period	5	1.01
Task-related training[a]	Number of hours of task-related training that the salesperson has undergone beyond the mandatory training hours	27.6	12.40
Growth-related training[a]	Number of hours of growth-related training that the salesperson has undergone beyond the mandatory training hours	18.8	11.60

[a]Yearly average values.
[b]Scaled by 10^2.

Equation 3. As for the control variables, we use the values in 2008 for the market size, tenure, regional dummies, and the competition level.

$$\begin{aligned}(3)\ \mathrm{SFV}^{\text{short term}}_{i,\,2008} &= \gamma_0 + \gamma_1\mathrm{Task\_Training}_{i,\,2004\rightarrow2007}\\ &+ \gamma_2\mathrm{Task\_Training}^2_{i,\,2004\rightarrow2007}\\ &+ \gamma_3\mathrm{Growth\_Training}_{i,\,2004\rightarrow2007}\\ &+ \gamma_4\mathrm{Growth\_Training}^2_{i,\,2004\rightarrow2007}\\ &+ \gamma_5(\mathrm{Task\_Training}\times\mathrm{Growth\_Training})_{i,\,2004\rightarrow2007}\\ &+ \gamma_6\mathrm{Monetary\_Inc}_{i,\,2004\rightarrow2007}\\ &+ \gamma_7\mathrm{Peer\_Recog}_{i,\,2004\rightarrow2007}\\ &+ \gamma_8(\mathrm{Monetary\_Inc}\times\mathrm{Peer\_Recog})_{i,\,2004\rightarrow2007}\\ &+ \Psi_k\mathrm{CTRL}_{ik,\,2008} + \varepsilon^{(SFV)}_{2i},\end{aligned}$$

where

$\mathrm{SFV}^{\text{short-term}}_{i,2008}$ = future value of salesperson i in the short run (2008),

$\mathrm{CTRL}_{ik,2008}$ = control variables (in 2008) as described previously,

$\gamma_0 - \gamma_8, \Psi_k$ = parameters to be estimated, and

$\varepsilon^{(SFV)}_{2i}$ = disturbance term associated with $\mathrm{SFV}^{\text{short-term}}_{i,2008}$.

To account for varying time horizons considered by the sales manager/firm, we estimate Equations 2 and 3 separately. The first estimation captures the impact of training and incentives on profits in long-term SFV, and the second estimation assesses the impact of the proposed effects in short-term SFV. The estimation of two temporally distinct models enables us to elicit any differences in the effects that may occur in the model using one-year and three-year horizons. From the firm's perspective, this would help managers decide which time horizon to adopt when managing the salesperson.

Modeling Challenges

Endogeneity. The opt-in nature of the training interventions creates a potential endogeneity bias in the task-related and growth-related training variables. It is possible that salespeople might strategically choose certain types of training on the basis of the market demand or their perceptions of the effectiveness of the training intervention, thereby leading to biased parameter estimates in Equations 2 and 3. We use an instrumental variable approach to adjust for the potential endogeneity bias in the training intervention variables.[4] To address the endogeneity in training interventions, we use the number of salespeople who opt in to each training type as a proxy for peer influence on the salesperson, which serves as an instrument for each training intervention type (growth and task training). The psychology and management literature streams have documented the influence of peers on people's attitudes and decisions (Burkhardt 1994; Salancik and Pfeffer 1978). In a sales setting, peer influence is known to influence the salesperson's technology adoption behavior (Jelinek et al. 2006; Schillewaert et al. 2005). Furthermore, Lim and Chen (2014) show the importance of considering social influence when designing incentive programs for salespeople. We posit that social influences play a role not only for incentive management but also for training interventions. In the context of this study, before opting in to a training program, a salesperson is likely to consider the success (measured in opt-ins) of previous training programs and decide accordingly. Drawing from prior research, we expect that the level of opt-ins for previous training programs increases a salesperson's propensity to opt in to a training session in the current time period. Furthermore, the popularity of a training program is unlikely to be correlated with the overall future performance of a specific salesperson because the salesperson's performance depends on his or her own abilities and motivations rather than the number of colleagues who underwent the same training intervention. In Equations 4a and 4b, we specify the endogenous equations, where peer opt-ins for each training intervention type (task related and growth related) are measured as the annualized average of the number of opt-ins for prior training interventions for the corresponding salesperson.

$$\text{(4a)}\quad \mathrm{Task\_Training}_{i,2004\rightarrow2007} = \delta_1 + \delta_2(\mathrm{Peer\_opt\_ins})^{\mathrm{Task\_Training}}_{i,2004\rightarrow2007} + \eta_{1i}, \text{ and}$$

$$\text{(4b)}\quad \mathrm{Growth\_Training}_{i,2004\rightarrow2007} = \theta_1 + \theta_2(\mathrm{Peer\_opt\_ins})^{\mathrm{Growth\_Training}}_{i,2004\rightarrow2007} + \eta_{2i}.$$

Heterogeneity. The second major modeling challenge that must be addressed is the issue of heterogeneity within the sales force. Accounting for observed and unobserved heterogeneity has long been viewed as critical when modeling marketing data. It has been shown to be important for researchers modeling salesperson performance as well as for salespeople handling multiple territories and markets of varying sizes and potentials (Cain, Bradlow, and Lodish 2013). We account for observed heterogeneity through the control variables (i.e., tenure with the firm, regional dummies, market size, and competition level) used in the model. To account for unobserved heterogeneity, we use a latent class modeling approach, which enables us to identify distinct segments among salespeople on the basis of their sensitivity to different kinds of organizational factors (e.g., opt-in training, incentive management). We believe that the use of a latent class structure (rather than a random- or fixed-effects specification) also enables us to develop managerially relevant segments, which would increase the practical applicability of our model.

Estimation

To estimate the parameters in Equations 2 and 3, and accounting for endogeneity within the same framework, we follow a two-step procedure. The first step in the estimation process is to regress the instrumental variables on the

[4]Another method to address endogeneity without the use of instruments is the latent instrumental variable approach developed by Ebbes et al. (2005), which uses latent class–style estimation. In the current context, an empirical identification issue exists when estimating the latent instrumental variable as well as latent class segmentation within the same model framework. For this reason, we resort to the instrumental variable approach to account for endogeneity.

endogenous variables (Equations 4a and 4b). The predicted values of task and growth training are hereinafter used as independent variables in Equations 2 and 3. The next step is to include the latent class modeling within the estimation procedure. We next specify the relative size of salesperson segment m (assuming there are M segments in the data) as

$$f_m = \frac{\exp(\lambda_m)}{\Sigma_m \exp(\lambda_m)}, \tag{5}$$

where λ_m = size of the segment m as a percentage of the total population size. The final likelihood of the latent class model for Equations 2 and 3 is given as

$$L(Q) = \Sigma_m f_m \times L(Q|m), \tag{6}$$

where $L(Q|m)$ = likelihood of model given that the segment membership is m.

We estimated the proposed model using the FlexMix subroutine in the R software (Grün and Leisch 2008). To maximize the likelihood in Equation 6, we employ an iterated expectation-maximization algorithm in which the estimation and maximization steps are repeated until the likelihood between iterations is minimal. We estimated the segment-level parameters conditional on the total number of segments (latent classes), which we determined exogenously. We implement the suggested estimation procedure twice, once for the short-term SFV (Equation 3) and again for the long-term SFV (Equation 2), and discuss the results of the estimation in the following section.

ESTIMATION RESULTS

We report results for Segments 1, 2, and 3 and compare the models using the log-marginal likelihood values and the Akaike information criterion (AIC) (Nylund, Asparouhov, and Muthén 2007). As stated previously, we estimated the proposed model twice: first to capture the short-term SFV (one-year horizon) and again to capture the effects on the long-term SFV (three-year horizon). Using the AIC and log-marginal likelihood as the basis, we select a two-class model as the best fit for our model for both dependent variable measures (for log-likelihood and AIC values, see Table 2).

Table 3 presents the parameter estimates for the proposed models. We report the R^2 values for each equation and each segment. From the results, we observe that the variance explained by our proposed drivers varies from .56 to .60. Next, we present and discuss the results for the short-term (one-year horizon) and long-term (three-year horizon) SFV models.

Table 2
RESULTS FROM LATENT CLASS ANALYSIS

Model	*Number of Segments*	*Log-Likelihood*	*AIC*
Short-term SFV	1	–1,574	3,028
(one-year horizon)	2	–1,342	2,744
	3	–1,521	3,102
Long-term SFV	1	–1,627	3,314
(three-year horizon)	2	–1,396	2,852
	3	–1,521	3,108

Training Effects

With regard to the main effects of training type (task and growth) on SFV, we find that the effect is positive and significant in the short run as well as the long run. Table 3 shows that task-related training has a positive main effect on long-term SFV (Segment 1: b = 1.292, $p < .01$; Segment 2: b = .448, $p < .01$) and a significant negative squared term effect (Segment 1: b = –.021, $p < .05$; Segment 2: b = –.014, $p < .01$). This implies a curvilinear (concave) relationship between task-related training level (in hours) and the long-term SFV. Specifically, the marginal increase in a salesperson's future value in the long run diminishes as he or she continues training to increase task-related KSAs. Using the parameter estimates for the main effect and the squared term effect (and holding all other variables constant), we can compute the optimal task training required for each segment to achieve greater long-term SFV. We find that the optimal task training required for Segment 1 (sensitive to training) is 30 hours, whereas the optimal point for Segment 2 (sensitive to incentives) is 16 hours. Using this information, and equipped with the knowledge of which salesperson belongs to which segment, managers can design optimal "ceilings" for each segment such that a salesperson can opt in to only a finite number of training sessions so as to maximize SFV. Furthermore, we find that the main effect for task training on short-term SFV is positive and significant (Segment 1: b = .664, $p < .01$; Segment 2: b = .230, $p < .01$), whereas the squared term is significant and negative (Segment 1: b = –.011, $p < .05$; Segment 2: b = –.007, $p < .05$). These parameter estimates suggest that task training has a nonlinear effect of salesperson future performance in the short run as well as the long run, thus confirming H_{1a}. Similarly, the impact of growth-related training on long-term SFV shows a significant main effect (Segment 1: b = 1.386, $p < .01$; Segment 2: b = .742, $p < .01$) and significant squared term (negative) effect (Segment 1: b = –.025, $p < .05$; Segment 2: b = –.021, $p < .05$). Thus, the impact of growth-related training on long-term SFV is also curvilinear (concave) and increases until a saturation point after which it plateaus, in support of H_{1b} in the long run. Similar to the task-related training effects, we compute the optimal growth training for each segment to achieve the greatest SFV. For Segment 1, we find that the optimal growth training is achieved at 27.72 hours, and for Segment 2 the optimal value is 17.66 hours. Furthermore, we find a similar curvilinear relationship between growth-related training hours and short-term SFV, in support of H_{1b} in the short run as well. To test the moderating role of growth training on the relationship between task training and SFV (H_{1c}), we turn to the interaction effect between the two variables. Table 3 shows that the proposed moderating effect of growth training is significant across both segments in the short- and long-term SFV equations, thus lending support to H_{1c}. In comparing the parameters across the two latent segments, we find that the main effect of task- and growth-related training interventions on long- and short-term SFV is higher for Segment 1 than for Segment 2, which indicates that the latent class model captures some of the unobserved heterogeneity among salespeople. There are two separate segments: Segment 1, in which SFV is more influenced by

Table 3
MODEL RESULTS FOR SFV (EQUATIONS 3 AND 4)

	Short-Term SFV (Annualized Average over One Year)				*Long-Term SFV (Annualized Average over Three Years)*			
	Segment 1 More Sensitive to Training N = 297		*Segment 2 More Sensitive to Incentives N = 186*		*Segment 1 More Sensitive to Training N = 306*		*Segment 2 More Sensitive to Incentives N = 178*	
	Estimate	*SE*	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
Intercept 1	9.100***	2.900	4.100***	1.030	21.300***	5.900	10.200***	3.100
Task training	.664***	.201	.230**	.103	1.292***	.039	.448**	.200
(Task training)^2	–.011***	.002	–.007***	.002	–.021***	.004	–.014***	.004
Growth training	.713***	.151	.382***	.054	1.386***	.294	.742***	.105
(Growth training)^2	–.013***	.001	–.011***	.002	–.025***	.002	–.021***	.004
Task training × Growth training	.086**	.038	.094**	.040	.168**	.074	.182**	.077
Monetary incentives[a]	1.361***	.275	1.876***	.345	.817***	.165	1.126***	.207
Nonmonetary incentives[b]	10.752***	2.408	13.895***	3.745	6.451***	1.445	8.337***	2.247
Monetary incentives × Nonmonetary incentives	.013**	.006	.020***	.007	.008***	.003	.012***	.004
Tenure with firm	4.200***	1.200	4.800***	1.400	5.300***	1.300	5.200***	1.100
Region dummy 1	.920**	.400	.310***	.060	1.100***	.400	2.500***	.560
Region dummy 2	–.116***	.041	1.060***	.310	–.210***	.050	.240***	.050
Region dummy 3	.261***	.059	–.720	.490	1.040**	.410	–.620**	.300
Region dummy 4	.710**	.360	–.907***	.038	.820*	.420	–.810	.560
Market size	.760***	.010	.050**	.020	.220***	.040	.180***	.030
Competition level	–.420***	.120	–.190*	.100	–.510**	.210	–.250	.170
R-square	.58		.60		.56		.58	

*$p < .1$.
**$p < .05$.
***$p < .01$.
[a]SFV and monetary incentives enter the equation in thousands of dollars to maintain the scale of the parameter estimates.
[b]Operationalized as peer recognition.

training interventions, and Segment 2, in which SFV is more influenced by incentives.

Incentive Effects

As we hypothesized in H_{2a}, monetary incentives positively influence SFV in the long run (Segment 1: b = .817, $p < .01$; Segment 2: b = 1.126, $p < .01$) as well as the short run (Segment 1: b = 1.361, $p < .01$; Segment 2: b = 1.876, $p < .01$). Because monetary incentives and SFV are measured in the same scale (thousands of dollars), we can interpret the coefficients as follows. A $1,000 increase in incentives leads to an $817 increase in long-term SFV for Segment 1, whereas the same incentive increase leads to a $1,126 increase in Segment 2's long-term SFV. Similarly, a $1,000 increase in monetary incentives leads to a $1,371 increase in short-term SFV for Segment 1 and a $1,876 increase in short-term SFV for Segment 2. In contrast to the effects of training, from the magnitude of the parameter estimates, we observe that the short-term impact of monetary incentives on short-term future profits is greater than its corresponding long-term effect across both segments.

With regard to the effect of nonmonetary incentives (peer recognition), we find that the effect of peer recognition on SFV is positive and significant in the long run (Segment 1: b = 6.451, $p < .01$; Segment 2: b = 8.337, $p < .01$) as well as in the short run (Segment 1: b = 10.752, $p < .01$; Segment 2: b = 13.895, $p < .01$), in support of H_{2b}. Furthermore, we find that the hypothesized synergistic effect of monetary and nonmonetary incentives (H_{2c}) is also positive and significant across both segments and time windows. From the magnitude of the parameter estimates, we observe that the effect of incentives on SFV is greater for Segment 2 than for Segment 1, irrespective of the time window being considered. This finding suggests that there is significant heterogeneity in the data, and the introduction of latent classes in the parameter estimation could elicit these differences. Finally, we find that the positive effect of monetary and nonmonetary incentives is greater in the short run than in the long run, which is consistent with prior literature.

DISCUSSION

In this study, we identify and bridge some of the knowledge gaps in the sales domain regarding the evaluation and management of salespeople. Specifically, our objectives are threefold: (1) to determine how the future potential of a salesperson should best be measured; (2) to identify and quantify the effect of organizational drivers, such as opt-in training and incentive management, of SFV; and (3) to suggest how to segment the sales force on the basis of salesperson responsiveness to the aforementioned drivers of future value. To achieve our objectives, we conduct a field study in collaboration with a B2B firm using longitudinal salesperson data. We propose a forward-looking, profit-oriented metric to value salespeople by drawing on CLV concepts. To our knowledge, this is the first study to examine salesperson value to the firm from this perspective. Furthermore, we outline the advantages of using SFV as a metric to measure the value of a salesperson in the sales organization while contrasting the proposed metric with existing popular metrics such as revenue and sales manager evaluations. Relying on various theories and psychological mechanisms from prior literature, we develop and test a set of hypotheses involving the drivers of SFV. Specifically, we quantify the impact of opt-in training interventions (task related and growth related) as well as incentives (monetary and nonmonetary) on SFV. Finally, we test the proposed framework on data from a B2B firm using a latent class modeling approach to account for unobserved heterogeneity. To account for the short-term versus long-term managerial focus, we study the impact of the proposed drivers on the short-term SFV (one-year horizon) as well as the long-term SFV (three-year horizon). By adopting a CRM-based approach to valuing the sales force, this research provides novel insights into the value of the salesperson as well as into how to manage the sales force to drive future profits.

Influencing a Salesperson's Future Performance Through Training and Incentive Management

In the field study, we find that monetary and nonmonetary incentives positively influence SFV. This result is consistent with expectancy theory as well as with prior research on salesperson performance (although prior research has used reflective measures rather than forward-looking measures). When presented with monetary incentives, salespeople are more motivated to expend effort toward the performance goal, thus increasing their profit potential to the firm. Furthermore, we find that nonmonetary incentives (measured as peer recognition) also have a positive influence on SFV. This result is in congruence with social reinforcement theory, which posits that in certain cases, people's motivation arises from the expectation of a public reward or recognition (e.g., "Employee of the Year") from their peers in the firm, thus increasing performance. We also find that there is a synergistic effect of monetary and nonmonetary incentives on the future profit potential of the salesperson. That is, salespeople perform better when their personal goals are driven by both monetary *and* nonmonetary rewards rather than by only one type of reward. Using these findings, firms can design more formalized modes and methods of recognizing salespeople because nonmonetary rewards have a significant effect on future performance. Whenever possible, managers should offer "customized" compensation to maximize SFV, focusing on what drives each salesperson. At minimum, to induce higher levels of extrinsic motivation and, eventually, future performance, firms should design compensation plans that factor in both monetary and nonmonetary rewards.

Turning to the effect of training interventions, we find that to increase future performance—and thus, SFV—the firm must account for heterogeneity in the sales force because there could be segments of salespeople who are more influenced by incentives or training. Drawing on prior conceptualization of training content, we identified two broad types of training that firms use to influence the salesperson's future performance: task-related training and growth-related training. To our knowledge, this is the first study to explicitly investigate the impact of training content and quantity on future profit from a salesperson. Specifically, we use four years of training data to study the impact of training interventions and show that task-related training interventions have a nonlinear effect on a salesperson's future performance in both the long run and the short run. We also show that the effect of task-related training on future performance is positive at first, but it reaches a saturation point, after which the positive effect begins to diminish. We also observe a similar nonlinear effect for growth-related training on SFV, implying that managers must keep in mind that there is a cutoff point with regard to training interventions, after which the marginal positive effect of increasing training diminishes. Too much training could reduce a salesperson's profit potential because the firm is investing a great deal of incremental dollars in training him or her with no positive gain resulting from that incremental training. Furthermore, as hypothesized, we find that growth-related training positively moderates the relationship between task-related training and future profit. From these results, managers should consider monitoring and even limiting a salesperson's opt-in behavior to reduce the risk of overtraining. One way to do so is to introduce ceilings on the number of hours and/or breadth of training interventions to which salespeople can opt in. Another way to reduce overtraining would be to provide some guidance to salespeople regarding the training they should consider in line with what the firm has observed from the results of other salespeople who have undergone various training opportunities. This guidance should encourage salespeople to sign up for only those training programs that are most likely to improve their selling performance in the future, which would minimize wasteful spending by the firm.

Segmenting the Sales Force

Our model captures unobserved heterogeneity among the salespeople through the latent class specification. A latent class specification enables us to identify underlying groups of salespeople with different characteristics (albeit a priori unknown) in the data and segment them accordingly. We show that there are two distinct "types" of salespeople that exhibit varying responses to training and incentives in both the short run and the long run. In our field study, Segment 2's SFV is affected more by incentives than that of Segment 1, whereas the influence of training on Segment 1 is greater than on Segment 2. Our findings underscore the importance of considering heterogeneity in the sales force with regard to the effect of training and incentives on future performance. In addition to assessing the impact of our independent variables on SFV, we also computed the SFV (post hoc) for each of the segments. In the short run, we find that the average short-term SFV for Segment 2 ($.273 million) is greater than that of Segment 1 ($.261 million). In the long run, we find that the SFV (annualized average over three years) of Segment 1 ($.296 million) is greater than that of Segment 2 ($.287 million). Although we do not propose hypotheses on any differences in SFV between the two segments, it is notable that the future profit contributions of the two segments also vary. One caution is that sales managers who have a short-term time orientation might look at a salesperson in Segment 2 and conclude that she performs better (compared with someone in Segment 1). However, our results indicate that a short-term view could be suboptimal because it ignores salespeople's long-term profit potential. Therefore, firms should encourage sales managers to adopt a holistic view of the salesperson (in the long run as well as the short run) to better understand the differences in the profit potential of each person in the sales force. Depending on the membership of the salesperson in each segment, sales managers can develop customized sales force management heuristics to define training level ceilings or provide monetary and nonmonetary incentives to improve each salesperson's future performance.

Accounting for Time Horizon of Reference

A unique element of this study is that we were able to examine both short-term (one-year) and long-term (three-year) time horizons with regard to a salesperson's future profit potential. In doing so, we uncover the drivers of salespeople's future short- and long-term profits and show that the organization should focus on different drivers depending on their time horizon. Our results help us provide suggestions to marketing practice on the basis of the time orientation of the firm. We find that the effect of training interventions on salesperson profitability is greater in the long run than in the short run. However, we also find that the effect of incentives on future profits is greater in the short run than in the long run. Thus, depending on the time orientation of the firm, managers can choose to modify the salesperson's behavior using the appropriate drivers identified. Sales managers can further use this information when forecasting and setting goals for their salespeople.

IMPLICATIONS

The results of our study have several potential implications for sales managers who use CRM systems to proactively manage the customers as well as the sales force. Advanced CRM systems (e.g., Siebel, Salesforce.com) that already implement the CLV metric could easily adopt the SFV metric because of the inherent dependence between the SFV and the CLV metrics. The results presented in this study can assist sales managers in various aspects of sales force management, such as salesperson hiring/selection, salesperson career development, and managing salesperson churn. Furthermore, by studying the magnitude of the effects in the proposed model, firms could also assess the return on investment of training and incentive management.

Personnel Selection

Using the SFV metric, firms can identify which salesperson in their sales force is likely to be the most profitable in the future. Analogous to customer acquisition using a CLV-based approach, if the firm is able to profile the "top" SFV candidate using internal demographic or psychographic variables for those people, it is also possible to extend the results to new hiring procedures. In the hiring process, firms can look for specific characteristics of top salespeople (after profiling their high-SFV salespeople) and make more informed hiring decisions that include the profit potential of the applicant. Note that due to lack of data, we do not dynamically model the uncertainty in SFV forecasts at the salesperson level. In certain situations, it is possible that the firm may be better off hiring a medium-SFV salesperson with higher uncertainty with the hope of discovering potential. We leave the exploration of this avenue of sales force management to further research.

Managing Salesperson Retention

Sales managers are often faced with decisions regarding which salespeople to retain and which to let go. In such situations, managers typically use reflective measures of performance such as previous performance evaluations, past revenue, key accounts managed, and their own intuition to make decisions about whom to let go. Our research has shown that in some cases, reflective measures could prove myopic and expensive for the firm because significant investments have already been made toward developing the salesperson. The proposed SFV metric would reduce this uncertainty to a great extent because it is a projection of the salesperson's profit potential after accounting for the firm's developmental costs. Furthermore, because we are able to provide implications for varying time horizons, managers with a short-term or a long-term focus can manage the sales force accordingly.

Salesperson Career Development

In addition to proposing the SFV metric, we quantify the effect of training (task related and growth related) and incentives (monetary and nonmonetary) on a salesperson's future value. By implementing the proposed SFV framework, the firm can not only identify the better salesperson but also realize *why* a salesperson's profit potential is plateauing/decreasing while another salesperson's future performance is high. Specifically, depending on the segment (training driven or incentive driven) to which the salesperson belongs, the manager can define ceilings/limits for opt-in training sessions or motivate the salesperson through monetary or nonmonetary incentives such that SFV is increased. Sales managers and supervisors play a vital role in the development of the salesperson (Cron 1984; Flaherty and Pappas 2000). In the case of an underperforming salesperson, the manager can use the proposed drivers to modify the salesperson's behavior. The implications of this research also can be extended to address the overspending problem. There could be situations in the marketplace in which the salesperson's future value is low because the cost structures are too high. For example, the firm could be investing in training (growth related and task related) for the salesperson when the employee in question is actually more incentive driven than training driven (Segment 2). With the right ceilings/limits for opt-in training sessions in place, managers can avoid the overspending problem in training interventions. Furthermore, the firm could provide incentives such as commissions or bonuses to motivate the salesperson to perform.

LIMITATIONS AND OPPORTUNITIES FOR FURTHER RESEARCH

We believe that this research provides novel insights and addresses some of the knowledge gaps in the sales management literature by proposing a CRM-based approach to better understand the future value of a salesperson. By proposing SFV as a metric to evaluate the future value of a salesperson, we believe that this article opens several avenues for additional research. For example, the proposed framework could be applied across various business settings (e.g., business-to-customer industries, other B2B industries) to explore similarities and differences across the two industries. Furthermore, in the current study, we link organizational factors (training and incentives) to a salesperson's future performance but do not investigate the role of the salesperson's cognitive and attitudinal elements (e.g., motivation, ability/aptitude) that could mediate the effect between organizational variables and SFV. From a modeling perspective, we adopt a closed-form modeling approach to assess the drivers of SFV.

Future studies could propose a structural model that describes the salesperson's behavior and further investigate how our proposed drivers affect SFV. This line of study could also yield theoretically grounded policy simulations of firm actions and their corresponding impact on SFV. Although the proposed model accounts for varying focal time horizons (one year vs. three years) in the analysis, it does not explicitly account for dynamics in the parameter estimates. Scholars could adopt a dynamic model to describe the time-varying effects of the parameters in a more "continuous" sense, thereby building on this research stream. Furthermore, this dynamic approach could also address the uncertainty or risk in a salesperson's future behavior. According to the recommendations from our study, the firm should recruit and manage salespeople with a high future value. However, in certain cases, it might be more affordable to recruit a salesperson with medium future value and aim to discover potential through training and/or incentives. Further research could develop a structural model to dynamically exploit this uncertainty/risk in salesperson future behavior.

Our implementation of the SFV metric involves simplifying the formulation such that P(Churn) = 0 (because no salesperson churned during our field study). Further research could use data from a company that experienced churn, explicitly model the drivers of salesperson churn, and incorporate these data into the SFV model. Prior work on salesperson turnover has provided some directions to understand the drivers of salesperson churn probability (Sager, Futrell, and Varadarajan 1989). Of special interest are organizational factors that influence the salesperson's churn. Specifically, research has found the salesperson's satisfaction regarding job perceptions (e.g., pay, promotion, supervision, work, coworkers) to be a leading indicator of salesperson turnover (Hom et al. 1992). Furthermore, Brashear, Manolis, and Brooks (2005) demonstrate that the effects of supervisor trust and perceived fairness predict salesperson turnover. In the current implementation, we correct for endogeneity bias in training interventions using an instrumental variable approach but refrain from overstating our results by making causal inferences. Further research could explore more robust endogeneity correction methods, such as the latent instrument variable (Ebbes et al. 2005) or control function (Petrin and Train 2010) approaches to account for the endogeneity bias.

A possible limitation of our study is in its applicability in business settings in which the firm has finite production capacities. In such cases, firms (especially in the manufacturing industry) typically use a regressive commission rate system that reduces bonuses/incentives to the salesperson after he or she has reached a stipulated quota, because firms could have difficulty handling the surplus of orders. In such situations, a sales quota–based system would work better. Further research could investigate how firms in this situation might be able to incorporate a forward-looking, profit-oriented metric. Finally, in our implementation, we observe that peer recognition has a positive influence on SFV. Sales managers use multiple modes of recognition, formal as well as informal, to reward the various performance levels and accomplishments of their salespeople. Further research could investigate the generalizability of our results by studying other conceptualizations of nonmonetary incentives that companies commonly use in the sales force management context or even suggest novel ways to provide rewards in this context.

APPENDIX: CLV ESTIMATION

Following Kumar et al. (2008)'s formulation, we compute CLV for existing customers using the following formula:

$$\text{(A1)} \quad CLV_i = \sum_{k=t+1}^{t+T} \frac{p(Buy_{ik}=1)\times \widehat{CM}_{ik}}{(1+r)^{k-t}} - \frac{\widehat{MT}_{ik}\times \overline{MC}}{(1+r)^{k-t}},$$

where

CLV_i = lifetime value for customer i, served by salesperson j;
$P(Buy_{ik} = 1)$ = predicted probability that customer i will purchase in time period k;
$\widehat{CM}_{ik}$ = predicted contribution margin provided by customer i in time period k;
$\widehat{MT}_{ik}$ = predicted level of marketing contacts directed toward customer i in time period k;
$\overline{MC}$ = average cost for a single marketing contact;
k = index for time period (months);
t = marks the end of the observation window; and
r = monthly discount rate, .0125 in the current case (15% annually).

To compute CLV using Equation A1, we require predictions of (1) marketing contacts, (2) the customer's purchase propensity, and (3) contribution margin provided by the customer given purchase. We model purchase propensity and contribution margin modeled using a Type II Tobit specification where the first selection equation is specified as using a logit model $[p(Buy_{ik} = 1)]$. The second level of the equation is specified in the linear form $\widehat{CM}_{ik}$. We specify the customer's latent utility of purchase as Buy^*_{ik}. Because we only observe purchase occasions (I_{ik}) and not the latent utilities, we treat this as a binary probit choice model wherein $I_{ik} = 1$ if $Buy^*_{ik} \geq 0$ and $I_{ik} = 0$ if $Buy^*_{ik} < 0$. We can thus parameterize Buy^*_{ik} in the following manner:

$$\text{(A2)} \quad Buy^*_{ik} = x^T_{i1k}\zeta_2 + u_{i1k}.$$

The second level of the Type II Tobit model involves a specifying $\widehat{CM}_{ik}$ as a linear function of covariates (Equation A3) conditional on the result of the Buy^*_{ik} model. The correlation between the two equations is captured with the inverse Mills ratio (λ):

$$\text{(A3)} \quad \widehat{CM}^*_{ik} = x^T_{i2k}\zeta_2 + u_{i2k}.$$

We model marketing contacts $\widehat{MT}_{ik}$ in the logarithmic form to account for the diminishing returns of marketing efforts as well (Venkatesan and Kumar 2004), as depicted in Equation A4:

$$\text{(A4)} \quad \log\left(1+\widehat{MT}_{ik}\right) = x^T_{i3k}\zeta_3 + u_{i3k}.$$

We included customer-specific exchange characteristics as well as firm-level variables based as independent variables for our predictions of propensity to buy, contribution margin, and marketing contacts. We based our choice of independent variables on practical considerations and prior research in the CLV literature stream (for a detailed discussion, see Kumar et al. 2008; Venkatesan and Kumar 2004). Table A1 presents a summary of the variables used for the CLV model calibration.

We then validate the proposed CLV model (estimated using data from 2004–2006) against actual customer-level purchase data for the following year (January 2007–December 2007) and calibrated it to improve to predictive accuracy. We used the MAPE to gauge the predictive accuracy of our model, defined using the following formula and expressed as a percentage:

$$\text{(A5)} \qquad \text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\text{Actual profit}_i - \text{CLV}_i}{\text{Actual profit}_i}\right|.$$

When assessing the predictive accuracy of the CLV model for 2007, we arrived at a MAPE of 9.8%. We conclude that our model performs sufficiently well in predicting the customer's future profits. Next, we summed the predicted profitability (measured as CLV) for each of the existing customers i per salesperson j to arrive at the customer equity from existing customers for each salesperson in the sample:

$$\text{(A6)} \qquad \text{CE}_j^{\text{existing}} = \sum_{i}^{N}\text{CLV}_{ij}.$$

To account for the new clients that each salesperson acquires, we compute the average annual acquisition rate (the average number of new customers for salesperson j from 2004 to 2007) for each salesperson and multiply it by the average CLV of the customers served by that salesperson for the period 2008–2010. That is,

$$\text{(A7)} \qquad \text{CE}_j^{\text{new}} = \text{annual Aquisition rate}_j \times \frac{\sum_{i}^{N}\text{CLV}_{ij}}{N}.$$

We use $\text{CE}_j^{\text{existing}}$ and CE_j^{new} in Equation 1c to compute the SFV of a salesperson.

Table A1

VARIABLES USED IN CLV ESTIMATION

	Exchange Characteristics	
Variable	*Definition*	*Firmographic Variables*
Level of marketing communications	Number of firm-initiated marketing touches in a given month	Industry type
Product purchase	Indicator variable = 1 if product is purchased, 0 otherwise	
Number of purchases	Number of purchase transactions in a given month	Number of years since incorporation
Recency	Time (in months) since previous purchase	
Contribution margin	Amount of profit ($) contributed by a customer in a given month	Domestic or multinational
Spending level	Share of wallet	
Multichannel behavior	Number of channels a customer uses to transact in a given year	Number of employees
Majority product category	Indicator variable = 1 if customer makes a purchase in a prespecified majority product category in a given year, 0 otherwise	
Cross-buying	Total number of product categories a customer purchases in a given year	Average annual revenue
Product returns	Amount of returns ($) a customer makes in a given year	Segment type (based on company size)
Referral credit earned	Amount of credit ($) earned due to referrals in a given year	Number of branch offices

REFERENCES

Ahearne, Michael, Ronald Jelinek, and Adam Rapp (2005), "Moving Beyond the Direct Effect of SFA Adoption on Salesperson Performance: Training and Support as Key Moderating Factors," *Industrial Marketing Management*, 34 (4), 379–88.

——, Son K. Lam, John E. Mathieu, and Willy Bolander (2010), "Why Are Some Salespeople Better at Adapting to Organizational Change?" *Journal of Marketing*, 74 (May), 65–79.

Apasu, Yao (1987), "The Importance of Value Structures in the Perception of Rewards by Industrial Salespersons," *Journal of the Academy of Marketing Science*, 15 (1), 1–10.

Armstrong, J. Scott and Fred Collopy (1992), "Error Measures for Generalizing About Forecasting Methods: Empirical Comparisons," *International Journal of Forecasting*, 8 (1), 69–80.

Attia, Ashraf M., Earl D. Honeycutt Jr., and Magdy Mohamed Attia (2002), "The Difficulties of Evaluating Sales Training," *Industrial Marketing Management*, 31 (3), 253–59.

Behrman, Douglas N. and William D. Perreault (1982), "Measuring the Performance of Industrial Salespersons," *Journal of Business Research*, 10 (3), 355–70.

Bendapudi, Neeli and Robert P. Leone (2002), "Managing Business-to-Business Customer Relationships Following Key Contact Employee Turnover in a Vendor Firm," *Journal of Marketing*, 66 (April), 83–101.

Brashear, Thomas G., Chris Manolis, and Charles M. Brooks (2005), "The Effects of Control, Trust, and Justice on Salesperson Turnover," *Journal of Business Research*, 58 (3), 241–49.

Burkhardt, Marlene E. (1994), "Social Interaction Effects Following a Technological Change: A Longitudinal Investigation," *Academy of Management Journal*, 37 (4), 869–98.

Cain, Lisa, Eric Bradlow, and Leonard Lodish (2013), "Who's #1? Accounting for Heterogeneity in Sales Force Performance Evaluation," working paper, The Wharton School, University of Pennsylvania.

Caldieraro, Fabio and Anne T. Coughlan (2002), "Channel Training Strategies in High-Technology Industries," working paper, Santa Clara University.

Churchill, Gilbert A., Neil M. Ford, and Orville C. Walker (1997), *Sales Force Management*, 5th ed. Chicago: Irwin.

Coughlan, Anne T. and Chakravarthi Narasimhan (1992), "An Empirical Analysis of Sales-Force Compensation Plans," *Journal of Business*, 65 (1), 93–121.

Cron, William L. (1984), "Industrial Salesperson Development: A Career Stages Perspective," *Journal of Marketing*, 48 (October), 41–52.

——, Greg W. Marshall, Jagdip Singh, Rosann L. Spiro, and Harish Sujan (2005), "Salesperson Selection, Training, and Development: Trends, Implications, and Research Opportunities," *Journal of Personal Selling and Sales Management*, 25 (2), 124–36.

Dubinsky, Alan J. (1981), "The Effects of Sales Training," *Industrial Marketing Management*, 10 (2), 129–37.

Ebbes, Peter, Michel Wedel, Ulf Böckenholt, and Ton Steerneman (2005), "Solving and Testing for Regressor-Error (In)Dependence When No Instrumental Variables Are Available: With New Evidence for the Effect of Education on Income," *Quantitative Marketing and Economics*, 3 (4), 365–92.

Flaherty, Karen K. and James M. Pappas (2000), "The Role of Trust in Salesperson–Sales Manager Relationships," *Journal of Personal Selling & Sales Management*, 20 (4), 271–78.

Ford, Neil M., Gilbert A. Churchill, and Orville C. Walker (1985), "Differences in the Attractiveness of Alternative Rewards Among Industrial Salespeople: Additional Evidence," *Journal of Business Research*, 13 (2), 123–38.

Grün, Bettina and Friedrich Leisch (2008), "FlexMix Version 2: Finite Mixtures with Concomitant Variables and Varying and Constant Parameters," *Journal of Statistical Software*, 28 (4), 1–35.

Gupta, Sunil, Dominique Hanssens, Bruce Hardie, Wiliam Kahn, V. Kumar, Nathaniel Lin, et al. (2006), "Modeling Customer Lifetime Value," *Journal of Service Research*, 9 (2), 139–55.

—— and Donald R. Lehmann (2005), *Managing Customers as Investments: The Strategic Value of Customers in the Long Run*. Upper Saddle River, NJ: Wharton School Publishing.

Hom, Peter W., Fanny Caranikas-Walker, Gregory E. Prussia, and Rodger W. Griffeth (1992), "A Meta-Analytical Structural Equations Analysis of a Model of Employee Turnover," *Journal of Applied Psychology*, 77 (6), 890–909.

Hughes, Douglas E., Joël Bon, and Adam Rapp (2013), "Gaining and Leveraging Customer-Based Competitive Intelligence: The Pivotal Role of Social Capital and Salesperson Adaptive Selling Skills," *Journal of the Academy of Marketing Science*, 41 (1), 91–110.

Jaramillo, Fernando, François A. Carrillat, and William B. Locander (2005), "A Meta-Analytic Comparison of Managerial Ratings and Self-Evaluations," *Journal of Personal Selling & Sales Management*, 25 (4), 315–28.

Jelinek, Ronald, Michael Ahearne, John Mathieu, and Niels Schillewaert (2006), "A Longitudinal Examination of Individual, Organizational, and Contextual Factors on Sales Technology Adoption and Job Performance," *Journal of Marketing Theory & Practice*, 14 (1), 7–23.

Jones, Eli, Lawrence Chonko, Deva Rangarajan, and James Roberts (2007), "The Role of Overload on Job Attitudes, Turnover Intentions, and Salesperson Performance," *Journal of Business Research*, 60 (7), 663–71.

Kanfer, Ruth and Phillip L Ackerman (2005), "Work Competence," in *Handbook of Competence and Motivation*, Andrew J. Elliot and Carol S. Dweck, eds. New York: Guilford Press.

Kohli, Ajay K., Tasadduq A. Shervani, and Goutam N. Challagalla (1998), "Learning and Performance Orientation of Salespeople: The Role of Supervisors," *Journal of Marketing Research*, 35 (May), 263–74.

Krishnamoorthy, Anand, Sanjog Misra, and Ashutosh Prasad (2005), "Scheduling Sales Force Training: Theory and Evidence," *International Journal of Research in Marketing*, 22 (4), 427–40.

Kumar, V. and Denish Shah (2009), "Expanding the Role of Marketing: From Customer Equity to Market Capitalization," *Journal of Marketing*, 73 (November), 119–36.

——, Rajkumar Venkatesan, Tim Bohling, and Denise Beckmann (2008), "The Power of CLV: Managing Customer Lifetime Value at IBM," *Marketing Science*, 27 (4), 585–99.

Lim, Noah and Hua Chen (2014), "When Do Group Incentives for Salespeople Work?" *Journal of Marketing Research*, 51 (June), 320–34.

McFarland, Richard G., Goutam N. Challagalla, and Tasadduq A. Shervani (2006), "Influence Tactics for Effective Adaptive Selling," *Journal of Marketing*, 70 (October), 103–117.

Miao, C. Fred, Kenneth R. Evans, and Zou Shaoming (2007), "The Role of Salesperson Motivation in Sales Control Systems—Intrinsic and Extrinsic Motivation Revisited," *Journal of Business Research*, 60 (5), 417–25.

Mintu-Wimsatt, Alma and Jule B. Gassenheimer (2004), "The Problem Solving Approach of International Salespeople: The Experience Effect," *Journal of Personal Selling & Sales Management*, 24 (1), 19–25.

Mobley, William H., Stanley O. Horner, and A.T. Hollingsworth (1978), "An Evaluation of Precursors of Hospital Employee Turnover," *Journal of Applied Psychology*, 63 (4), 408–414.

Neslin, Scott A., Sunil Gupta, Wagner Kamakura, Junxiang Lu, and Charlotte H. Mason (2006), "Defection Detection: Measuring and Understanding the Predictive Accuracy of Customer Churn Models," *Journal of Marketing Research*, 43 (May), 204–211.

Nonis, Sarath A. and Jeffrey K. Sager (2003), "Coping Strategy Profiles Used by Salespeople: Their Relationships with Personal Characteristics and Work Outcomes," *Journal of Personal Selling & Sales Management*, 23 (2), 139–50.

Nylund, Karen L., Tihomir Asparouhov, and Bengt O. Muthén (2007), "Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study," *Structural Equation Modeling: A Multidisciplinary Journal*, 14 (4), 535–69.

Oliver, Richard L. (1974), "Expectancy Theory Predictions of Salesmen's Performance," *Journal of Marketing Research*, 11 (August), 243–53.

Palmatier, Robert W., Lisa K. Scheer, and Jan-Benedict E.M. Steenkamp (2007), "Customer Loyalty to Whom? Managing the Benefits and Risks of Salesperson-Owned Loyalty," *Journal of Marketing Research*, 44 (May), 185–99.

Petrin, Amil and Kenneth Train (2010), "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47 (February), 3–13.

Rapp, Adam, Raj Agnihotri, and Thomas L. Baker (2011), "Conceptualizing Salesperson Competitive Intelligence: An Individual-Level Perspective," *Journal of Personal Selling and Sales Management*, 31 (2), 141–57.

Roman, Sergio, Salvador Ruiz, and Jose Luis Munuera (2002), "The Effects of Sales Training on Sales Force Activity," *European Journal of Marketing*, 36 (11/12), 1344–66.

Sager, Jeffrey K., Charles M. Futrell, and Rajan Varadarajan (1989), "Exploring Salesperson Turnover: A Causal Model," *Journal of Business Research*, 18 (4), 303–326.

——, P. Rajan Varadarajan, and Charles M. Futrell (1988), "Understanding Salesperson Turnover: A Partial Evaluation of Mobley's Turnover Process Model," *Journal of Personal Selling & Sales Management*, 8 (1), 21–35.

Salancik, Gerald R. and Jeffrey Pfeffer (1978), "A Social Information Processing Approach to Job Attitudes and Task Design," *Administrative Science Quarterly*, 23 (2), 224–53.

Salopek, J.J. (2009), "The Power of the Pyramid," *T & D Magazine*, 63 (5), 70–76.

Schillewaert, Niels, Michael J. Ahearne, Ruud T. Frambach, and Rudy K. Moenaert (2005), "The Adoption of Information Technology in the Sales Force," *Industrial Marketing Management*, 34 (4), 323–36.

Segalla, Michael, Dominique Rouziès, Madeleine Besson, and Barton A. Weitz (2006), "A Cross-National Investigation of Incentive Sales Compensation," *International Journal of Research in Marketing*, 23 (4), 419–33.

Stajkovic, Alexander D. and Fred Luthans (1997), "A Meta-Analysis of the Effects of Organizational Behavior Modification on Task Performance, 1975–95," *The Academy of Management Journal*, 40 (5), 1122–49.

Tanner, John F., Jr., Michael Ahearne, Thomas W. Leigh, Charlotte H. Mason, and William C. Moncrief (2005), "CRM in Sales-Intensive Organizations: A Review and Future Directions," *Journal of Personal Selling & Sales Management*, 25 (2), 169–80.

Venkatesan, Rajkumar and V. Kumar (2004), "A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy," *Journal of Marketing*, 68 (October), 106–125.

Walker, Orville C., Jr., Gilbert A. Churchill Jr., and Neil M. Ford (1977), "Motivation and Performance in Industrial Selling: Present Knowledge and Needed Research," *Journal of Marketing Research*, 14 (May), 156–68.

Weitz, Barton A. (1978), "Relationship Between Salesperson Performance and Understanding of Customer Decision Making," *Journal of Marketing Research*, 15 (November), 501–516.

——, Harish Sujan, and Mita Sujan (1986), "Knowledge, Motivation, and Adaptive Behavior: A Framework for Improving Selling Effectiveness," *Journal of Marketing*, 50 (October), 174–91.

Williamson, Nicholas C. (1983), "A Method for Determining the Causes of Salesperson Turnover," *Journal of Personal Selling & Sales Management*, 3 (1), 26–35.

Wilson, Phillip H., David Strutton, and M. Theodore Farris II (2002), "Investigating the Perceptual Aspect of Sales Training," *Journal of Personal Selling & Sales Management*, 22 (2), 77–86.

Zoltners, Andris A., Prabhakant Sinha, and Sally E. Lorimer (2008), "Salesforce Effectiveness: A Framework for Researchers and Practitioners," *Journal of Personal Selling & Sales Management*, 28 (2), 115–31.