LEVERAGING CUSTOMER-SALES FORCE INTERACTIONS TO CREATE FUTURE VALUE FOR THE FIRM

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Abstract

The salesperson-customer interaction is paramount, not only to the immediate transaction, but also to customer's future value for the firm. Despite this importance, meager research explicitly explores the effect of salespeople on customer's future visits. In this dissertation I examine the role of salespeople not only in bringing customers back for repeat purchases, but also in developing other revenue streams such as service from the same customers.

Essay 1 examines how using successful customer relationship strategies can spill over among salespeople. I report a unique quasi-experiment in which an upscale apparel retailer trains its salespeople to adopt B2B account management and relationship-building strategies and apply them to their customers hoping to bring them back to the store. I studied more than 1,400 salespeople at about 200 stores measuring the degree to which they engage in the specific relationship-building behavior, their pre- and post-training performances, and more than 30 individual- and store-level covariates over the years before and after the training. Moreover the stores fell into three categories: a) full stores wherein the entire sales force are trained to adopt the relationship building strategy, b) partial stores wherein only a subset of the salesforce are trained, and c) control stores in which no one is trained. I employed recently-developed matching methods to obviate selection bias from store- and individual-level analyses. Drawing from literature on information dissemination in competitive contexts as well as demographic diversity I hypothesized and found that (1) partial training can be as effective as full-training in stores with low performance diversity, (2) tenure homogeneity of the trained salespeople helps their individual outcomes but hurts the spillover of the relationship-building behavior to the untrained salespeople, and (3) untrained individuals with similar performances to the group of trained salespeople are more likely to adopt the relationship building behavior.

Essay 2 investigates whether what happens between salespeople and customers during a sales negotiation can affect customer's future value. In particular, I explored whether open negotiation, manifested by information disclosure by the seller, can affect customers' immediate future (e.g. cross-selling revenues, finance and insurance, etc.) and distant future (e.g. service encounters, repeat purchase) value.

Utilizing three sets of data, a primary data set with records of actual sales negotiations between salespeople and customers in more than 400 auto purchase transactions, a secondary data set with all the sales transactions of the same dealerships, and a dataset obtained from the service departments of those dealerships, I explored the role of open negotiation strategy on the backend gross profits and the likelihood of customers returning for service. I found that when salespeople disclose the invoice price of the customer's desired car, the frontend gross profits would predictably be significantly lower than when they did not disclose the invoice price. However, disclosing the invoice early in the negotiation significantly helped both the backend gross and service likelihood, compared to not disclosing or middle/late disclosure. I hypothesized that because the internet informs customers about invoice prices, early invoice disclosure in the frontend helps build customer trust, which firms manipulate in the backend of the deal for which far less information exists for customers. I also found that early disclosure significantly predicts service come-back, even after controlling for customer distance to the dealership. I also explored the moderating role of channel (internet vs. dealership) on the effect of open negotiation on customer future value.

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ESSAY 1

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INTRODUCTION

The importance of sales training to organizations is reflected in the staggering 15 billion dollars of estimated annual expenditure that U.S. corporations alone invest each year on sales force training programs, which amounts to about $2,000 per sales person per year (Ingram et al. 2015; Salopek 2009; SPI 2014). Training interventions play an integral role not only in gaining short-term productivity goals, but also in building a salesperson's future value to the firm (Kumar, Sunder, and Leone 2014). Besides improving sales effectiveness and productivity, training also enhances the firms' chances of retaining their salespeople as salespeople with inadequate training are more likely to feel conflict, ambiguity, and stress which contribute to voluntary turnover (Boles, Wood, and Johnson 2003; MacKenzie, Podsakoff, and Ahearne 1998). The American Society for Training and Development reports that companies that invest more than average in sales training are 10 times more likely to produce peak-performing salespeople than companies that do not, have 45% higher median total stockholder return than those that spend average and 85% higher than those that spend less than average (Bassi et al. 2000; Ingram et al. 2015).

Despite such benefits, training salespeople is not easy. Salespeople are often pressed for time, availability in territory is crucial for them, and it is difficult to align their schedules for training sessions. Moreover the opportunity cost of sales training is extremely high since a single sales call costs companies more than $200 on average – more than $400 for pharmaceutical firms and some other industries (Zoltners and Lorimer 2000). Hence devoting salespeople's time to anything but calling customers is tantamount to instant loss of money, even without accounting for the loss of potential sales that might had resulted from having salesperson on the floor. To compound the matters, most corporate-held sales trainings are in the form of off-site, multi-day events, making it even more challenging for sales managers to send their whole crew to such events. Corporations have traditionally relied on these events mostly to gather salespeople from different stores, territories, or branches and to retain the emphasis on role-playing and interactive live sessions that remain the hallmark of sales training (Lambert 2014; Robinson 1987).

Facing these challenges, many sales managers prefer to send only a *subset* of their sales force to training events. According to Sales Management Association, 63% of sales directors in leading sales organizations report that for each corporate-held training event, the majority of sales managers from different districts, stores, or branches send only a part of their salespeople to these events. Interviews with these directors revealed that although a few companies use criteria such as belonging to the same cohort of salespeople, tenure, ratings on customer satisfaction surveys, or performance to choose salespeople whom they want to train, the majority of companies had no specific formal criteria for selecting the trained group (SMA 2015).

This essay answers two questions: 1) whether any a priori characteristics of the sales force predict that training a part of the sales force will be as effective as training all of it, and if yes, 2) what composition of salespeople should be trained so that the entire store benefits from their training? This study extends current literature on sales force training which suffers from a dearth of relevant and updated work. The bulk of research on sales training is rooted in literature on employee training effectiveness from the 1950’s and 1960’s (Kirkpatrick 1959), focusing mostly on classroom content and training techniques that maximize the chances of the content being applied in the workplace (Churchill et al. 1985; Cron et al. 2005; Hawes 1982; Honeycutt and Stevenson 1989; LaForge and Dubinsky 1996).

To answer these questions, I report a field quasi-experiment on a national luxury apparel retailer that trains its salespeople to apply a relationship-building method on their previous clients. Stores in my sample are assigned to each of the following three conditions: a) full condition in which the full sales force is trained, b) partial condition in which a subset of the sales force is trained, and c) control condition in which no one is trained. I argue that the extent to which partial stores experience similar performance outcomes as full stores depends largely upon the degree to which training *spills over* from the trained to the untrained salespeople in partial stores.

The spillover effect of training however, is not obvious considering an important characteristic of salespeople which distinguishes them from regular employees – salespeople are in direct competition with each other. Even without formal sales contests and other comparative incentive systems with which salespeople are frequently motivated, salespeople in the same territories or with the same target markets compete with each other for the same customers.

Head to head competition can demotivate salespeople from sharing perceived valuable knowledge with each other. From a different perspective however, more competition can lead to a higher motivation to learn by *observing* methods used by rivals and trying to mimic them. A well-developed literature in economics documents how firms learn by closely following and mimicking their rivals' strategies (Chang and Xu 2008; Hsieh and Vermeulen 2013; Lieberman and Asaba 2006). More relevantly, lab studies have shown that when subjects can openly view the outcome of strategies used by others, competing groups can have similar outcomes as cooperating groups (Budescu and Maciejovsky 2005; Maciejovsky and Budescu 2013). Thus I expect that training spill better in more competitive stores.

Despite the competitive nature of the selling job, the severity of competition widely varies from store to store. Current literature on sales performance suggests that salespeople at different levels of performance (e.g. bottom, core, and top performers) are more likely to compete with salespeople at their same performance level and hence are motivated by different incentive systems (Chung, Steenburgh, and Sudhir 2014; Steenburgh and Ahearne 2012). This is consistent with the economic notion that *firms* with similar market positions and resources are more likely to form rivalries and mimic each other (Chen 1996; Lieberman and Asaba 2006). I hypothesize that stores in which the performance of salespeople is closer to each other are more competitive and provide higher motivation for the untrained salespeople to vicariously learn from their trained colleagues. I also found that individual salespeople who are more similar in performance to the group of trained salespeople are more likely to adopt the taught behavior.

On the other side of the training spillover, trained salespeople do not play a passive role and, under increased competition will protect their knowledge from being shared or observed by untrained peers. Prior research on group composition has shown that work units whose members have entered the organization about the same time communicate better and more frequently which leads to increased group cohesion, supportive relationships, and lower turnover rates (O'Reilly, Caldwell, and Barnett 1989; Pfeffer 1983; Williams and O'Reilly 1998). Especially in contexts such as sales where uncertainty abounds and other background variables might not have a significant variation, similarity in time of entry leads to increased communication as peers in the same cohort learn the ropes together, which in turn leads to identification with others of similar tenure (Moreland 1985; Williams and O'Reilly 1998).

While sending salespeople of the same cohort to the next training event is a rule of thumb for many managers, I hypothesized and found that doing so will concentrate all the more likely paths of communication in one group and increases within-group identification and between-group differentiation which blocks the spillover of training to outsiders. In contrast, arranging a group of salespeople with diverse tenure levels makes them more likely to be less protective of their knowledge in face of untrained peers with whom they identify.

Data collected from 1,470 salespeople in 209 stores over years, before and after the training, allowed me to track the degree to which salespeople used the taught behavior, their pre- and post-training performances, store sales and about 30 store- and individual-level covariates measured at both time periods. I carried out three sets of analyses: First, I compared stores with full-, partial-, and no-training policies with each other. To ensure that stores in each condition only randomly differed from one another prior to training I applied a newly developed matching method called marginal mean weighting with propensity score stratification (MMW-S). Next, I performed the "spillover" analysis comparing untrained salespeople in partial stores with salespeople in control (no-training) stores using the same matching method. I conducted my final set of analyses on individual salespeople in partial-training stores. To ensure that trained and untrained salespeople within the partial stores only randomly differed before the training, I matched them on more than 30 covariates using a propensity-score matching method based on “nearest neighbors”.

This essay contributes to both theory and practice of sales training in several distinctive ways. First, my findings offer direct objective instructions to managers on *when* to use either partial or full-training and *who* to train. Based on my findings, managers in performance-homogenous stores can save time and money by training a tenure-diverse group of salespeople instead of everyone. However in performance-diverse stores where spillover is less likely to occur, full-training is superior; if full-training was not feasible I find that training a tenure-homogenous group is superior to training a tenure-diverse group due to the individual performance boost of the homogenous group.

Second, to the best of my knowledge, no research has so far studied the extent to which spillover can be effective by comparing partially-trained groups with fully-trained groups in a field setting. Moreover, I extend current literature which presumes a passive role for the knowledge holder (i.e. trained salespeople in my case), focuses mostly on noncompetitive contexts, and measures exerted effort rather than the learning of specific strategies from peers. I employed a recently-developed matching method suitable for multivalued treatments (MMW-S) and my identification of spillover effect puts my research among the very few papers (mostly in economics) that investigate a violation of the stable unit treatment value assumption in causal inference (SUTVA; Rubin 1978). Finally, I contribute to the literature on sales force training by moving away from the over-researched area of training content to an equally-important problem of choosing the right composition of salespeople to train.

THEORETICAL BACKGROUND AND HYPOTHESES

Competition among Salespeople

Selling is one of the most competitive jobs on the planet. Even in the absence of sales contests or limited rewards to compete for, salespeople who target the same segment of customers have to steal customers from each other. Despite such inherent competition, a given district or store can have a more or less competitive climate according to the performance level of its salespeople. Current literature suggests that salespeople at different performance levels (e.g. bottom performers, middle performers, top performers) are more likely to see peers at their own level as direct rivals (Chung 2015; Chung, Steenburgh, and Sudhir 2014; Steenburgh and Ahearne 2012). Studies show that salespeople at different performance levels are so different that they are even motivated with different incentive structures (Chung, Steenburgh, and Sudhir 2013; Steenburgh and Ahearne 2012). While top performers are more likely to be motivated with over-achievement rewards and bonuses, mid-performers are more likely to be motivated by sales contests and bottom performers with quarterly bonuses (Chung, Steenburgh, and Sudhir 2014; Chung, Steenburgh, and Sudhir 2013; Steenburgh and Ahearne 2012).

Building on these findings, I argue that the more diverse a store is in sales performance (i.e. the more a store contains salespeople at all performance levels) the less competitive is the sales climate of the store. As the difference between performance levels shrinks in a store, salespeople find more peers at their own performance level and hence the sales climate becomes more competitive. Thus I operationalize store competition by prior performance diversity of a store with the less performance-diverse stores being more competitive.

Competition and Knowledge Spillover

Similar to salespeople at the same performance levels, a rich literature in economics and strategy posits that firms with comparable market positions and resource endowments view each other as direct rivals (Chen 1996; Lieberman and Asaba 2006). These firms closely monitor each others' behaviors and mimic specific strategies including innovation strategies (Greve and Taylor 2000), choice of location (Henisz and Delios 2001), organizational structure (Fligstein 1985), and market entry decisions (Hsieh and Vermeulen 2013). Moreover classical literature in microeconomics suggests that as the overall context becomes more competitive (e.g. moving from a monopoly to a perfect competition), information dissemination improves since firms have to learn from competitors to remain in the market while at the same time it becomes difficult to withhold knowledge from them (Bain 1968).

Despite the rich literature on knowledge spillover among firms, meager research exists on knowledge spillover among competing peers. Literature on informal learning (Tannenbaum et al. 2010) is mostly theoretical and studies teammates and cooperating peers. Literature on peer effects also mainly focuses on teams and non-competitive work groups, studying how peers affect each other in these contexts. For instance the introduction of a highly productive team member has shown to affect the productivity of teammates leading to either free-riding behavior or productivity boost under social pressure (Mas and Moretti 2009).

However, the peer effects literature suffers from two important gaps. First, the *effects* studied in peer effects literature have more to do with exerted effort than learning specific strategies. I close this gap by measuring the degree to which untrained salespeople use a specific method taught in the training as a direct proxy for learning effects. Moreover, this literature assumes a passive role for the knowledge holder. Increased competition motivates not only the uninformed parties to learn from the informed, but also the informed parties to withhold their knowledge from being shared or observed. To the best of my knowledge, no research so far has studied both dynamics.

Of particular relevance to my work are the series of lab experiments run by Budescu and Maciejovsky who studied information spillover in cooperative versus competitive settings (Budescu and Maciejovsky 2005; Maciejovsky and Budescu 2007; Maciejovsky and Budescu 2013). Rather than focusing on effort or motivation that is the center of most peer effects literature, these researchers study how the correct strategy to play a game spills from informed participants to uniformed ones in competitive settings. They find that under open feedback mechanism, a competitive group can have similar outcomes as a cooperative group. In other words, although informed participants have strong incentives not to divulge their information to other rivals, the public nature of the game prevents them from withholding it indefinitely (Maciejovsky and Budescu, 2007).

Demographic Homogeneity/Diversity and Group Cohesion

While prior research has mostly assumed a passive role for knowledge holders in spillover effects, I argue that the composition of the group of trained salespeople plays an integral role in training spillover. Most compositional researchers have long trumpeted the salutary effects of demographic homogeneity in teams and work groups.

Demographic variables studied in this literature are organizational tenure (O'Reilly, Caldwell, and Barnett 1989; Pfeffer 1983; Williams and O'Reilly 1998), age (Jackson et al. 1991; O'Reilly, Caldwell, and Barnett 1989), and gender and race (McGinn and Milkman 2013; Tsui, Egan, and O'Reilly 1992).

Homogenous groups communicate better and more frequently (Mesmer-Magnus and DeChurch 2009) which leads to group cohesion, supportive relationships, social ties, increased attachment to the group, and better performance (Chattopadhyay, George, and Shulman 2008; Tsui, Egan, and O'Reilly 1992; Williams and O'Reilly 1998). In contrast, heterogeneity is linked to organizational turnover (O'Reilly, Caldwell, and Barnett 1989), conflict and political activity (O’Reilly, Snyder, and Boothe 1993), and less effective communication (Tsui, Egan, and O'Reilly 1992; Williams and O'Reilly 1998).

I decided to focus on demographic homogeneity/diversity of the group of trained salespeople rather than other possible group characteristics for the following reasons. First, in answering what composition of salespeople more likely benefits the training spillover, I had to consider factors that facilitate social communication and attenuate competition between the trained and untrained salespeople. Focusing on other nonsocial variables ignores the motivation of trained salespeople to withhold their knowledge from peers. Second, demographic homogeneity/diversity variables are antecedents of other social phenomena such as social networks (Ibarra 1992). Third, these variables are more objective and hence more actionable than others. For instance, I recommend managers to select salespeople with diverse tenure levels in highly competitive stores. This is more feasible for a manager than guessing or surveying salespeople to find their network centrality or similar social variables and use those as the selection criteria.

However demographic homogeneity literature misses two important pieces. First, very much like the literature on peer effects, this literature studies cooperative groups such as teams or work groups. Second, the benefits of group homogeneity are shown primarily within one work unit or team rather than sub-groups within a work unit. I argue that in competitive contexts such as a sales unit, although the homogeneity of a sub-group within the bigger work unit might benefit individual performance of sub-group members, it hurts the spillover of knowledge to the rest of the unit.

The Moderating Role of Performance Diversity

The studies of Budescu and Maciejovsky found that uninformed participants experienced significantly improved performance when they interacted with at least one informed participant compared to a baseline of only uninformed participants. However, these outcomes were dependent upon receiving some form of public feedback (Maciejovsky and Budescu, 2007), much like a salesperson may experience by closely observing the methods used by peers. Thus, in competitive sales environments, where performance diversity is low, salespeople should be able to detect the winning strategies utilized by their trained counterparts because they spend a significant amount of time together on the sales floor. However, sales environments in which competition is low (i.e., performance diversity is high) will likely not benefit collectively from the training of a few individuals because a lack of urgency or motivation to actively observe and learn from others may exist. Competition provides a primary motivation to enhance one's selling abilities and increase individual performance. In its absence, there is little motivation for untrained employees to search for effective methods and strategies used by the trained group.

For instance in my context, the trained group are taught to send relationship building messages to consumers that they have helped before in hope of a repeat purchase. Now unless a strong motivation exists to closely monitor every move of the rivals, the usage of this strategy by the trained group can easily go completely undetected on the radar of the untrained peers. Even if the untrained salespeople observe the method used by their trained peers, they might still not realize its value unless they can link the success of the trained salespeople to their historical behavior and usage of this method by having them under close scrutiny. Such close scrutiny is only motivated in a highly competitive sales climate where salespeople's performances are close to each other.

In addition I anticipate that untrained salespeople who perform at a level similar to those who receive training will be strongly motivated to observe the behaviors of the trained salespeople and hence more likely to engage in the taught selling behaviors than those who perform at a dissimilar level.

> **H_1:** Performance diversity moderates the positive effects of training on **(a)** store sales per sq. foot, such that partial-training stores with low performance diversity will have greater increases in sales per sq. ft. than partial-training stores with high performance diversity; **(b)** sales-related behaviors, such that untrained salespeople within partially-trained stores are more likely to engage in behaviors learned by trained salespeople when performance diversity is low;
> **H_2:** Performance similarity to the group of trained salespeople will positively influence the behavior of untrained salespeople, such that untrained salespeople within partially trained stores are more likely to engage in behaviors learned by trained salespeople when their performance levels are similar versus dissimilar to the group of trained salespeople.
> **H_3: (the spillover hypothesis): (a)** Untrained salespeople in partial stores experience greater performance growth than those in non-training stores. (b) Performance diversity moderates the spillover effect such that the effect is amplified in stores with low performance diversity but eliminated in stores with high performance diversity.

The Moderating Role of Tenure Diversity of the Trained Group

Of all the other demographic variables studied in work group composition literature, tenure homogeneity/diversity has arguably enjoyed more attention with a plethora of studies confirming its significance in determining social integration, identification, and performance (see Williams and O’Reilly 1998 for a review). I focus on tenure diversity among other demographic variables since it is more relevant than other diversity measures to the type of group processes I are interested in including communication, cohesion, and information sharing. Other group diversity measures such as gender or race diversity are applied to different contexts such as promotion opportunities for minorities (McGinn and Milkman 2013) and evidence regarding their effects on group outcomes are weak and confounded (Williams and O’Reilly 1998). Many studies have found the significance of tenure diversity in affecting group processes while other diversity variables (e.g. age diversity) were not significant (O'Reilly, Caldwell, and Barnett 1989). Also similarity in tenure is almost always a salient feature in work groups while it might not be the case for other demographic variables whose salience depends on the context of the problem (Pfeffer 1983; Williams and O'Reilly 1998).

People with the same level of organizational tenure are in the same cohort, have entered the organization about the same time, and have learned the ropes together. These people communicate more with each other (Mesmer-Magnus and DeChurch 2009; Pfeffer 1983; Williams and O'Reilly 1998) which promotes identification and increased similarity (Pfeffer 1983; Williams and O'Reilly 1998). Tenure-homogeneous groups enjoy higher cohesion and social integration, better communication, higher interpersonal identification, lower propensity to live the group among members, and enhanced performance (Moreland 1985; O'Reilly, Caldwell, and Barnett 1989; Pfeffer 1983; Tsui, Egan, and O'Reilly 1992; Williams and O'Reilly 1998).

I argue that training salespeople who are in the same cohort or have close tenures will concentrate all the more probable paths of communication in one group. Doing so will also further strengthen their within-group identification since besides having similar tenures, they have also received the same training. As such, I hypothesize that training a tenure-homogenous group will have the following two, one positive and one negative, effects.

On the positive side, the homogenous group of trained salespeople is more likely to benefit from the training individually than a more diverse group of trained salespeople. Forces of competition are less likely to affect people who identify and communicate frequently with each other. Once they get back from the training, they are more likely to trouble-shoot the training material for each other or practice it together which in turn, increases the chances of effectively applying the training material at work and boosting their individual performance.

On the negative side however, a homogenous group of trained salespeople is less likely to facilitate knowledge spillover to the rest of the store. Their strengthened within-group identification makes them differentiate more from outsiders and hence more protective of their knowledge from being observed by the untrained salespeople, especially under more intense competition. Moreover, since the probable paths of communication are all concentrated in the group of homogenous trained salespeople, the spillover of knowledge is hampered even further. In contrast, a *diverse* group of salespeople will facilitate the spillover of training to the rest of the store. This is because each member of a team of tenure-diverse salespeople has similar others outside the trained group with whom they identify and communicate more. This makes them less protective and even more open to share their knowledge with those similar others who have not received the training.

I argue that what makes either of the above effects more dominant is the degree of competition. As I hypothesized earlier, spillover is more likely in stores with low performance diversity (highly competitive). Therefore I hypothesize that for these stores, training a tenure-*diverse* group of salespeople is more beneficial since they facilitate the spillover of the training. In contrast, in stores with high performance diversity (noncompetitive) where spillover is less likely to happen, training a tenure-homogenous group is better.

H_4: Within partial-training stores, tenure diversity of the trained salespeople moderates the positive effects of:

(a) low performance diversity on increase in store sales per sq. foot, such that increases in store sales per sq. foot are amplified in stores with low performance diversity and diminished in stores with high performance diversity when tenure diversity is high.

(b) low performance diversity on sales-related behaviors, such that untrained salespeople are more likely to engage in behaviors learned by trained salespeople whose tenure diversity is high.

(c) performance similarity to the trained salespeople on sales-related behaviors of untrained salespeople, such that this relationship is amplified when tenure diversity is high.

METHOD

Research Context

The data comes from a national chain retailer that sells upscale women's apparel. The retailing context demonstrates characteristics that are extremely germane to my line of research and hence desirable for testing my hypotheses. First, corporate-held training events for salespeople are very common in retailing. Second, store salespeople spend a lot of time together which makes them susceptible to all kinds of knowledge spillover and observational learning. Finally, because the customer is physically present in the store, the competition among salespeople to gain her attention first is sensed more than contexts where salespeople call on random, non-present customers (e.g. a call center).

Training

The training was an off-site, half-a-week event focusing on how to build a personal clientele list and engage with customers using personalized notes and messages. The idea behind this training stemmed from traditional relationship-building activities taught and used for decades in business-to-business industries. With some more upscale retailers in the industry starting to teach and use these “old school” customer relationship management techniques in the fresh setting of retailing, the training emphasized applying these techniques using a few new tools such as Twitter, Facebook, and mobile texts. The training was held at a desirable regional location and included lodging, meals, and entertainment.

Salespeople were trained to act as account managers and communication bridges between the store and the customer, keeping track of the customers’ style, size, and taste and sending them personalized messages regarding new offerings that fitted their customers’ preferences, special discounts tailored to their customers, or simple updates. Trained salespeople were expected to send personalized, relationship-enhancing messages to a significantly higher percentage of their customers than the untrained salespeople. Trained salespeople were also more likely to improve their performance than the untrained since the returned customer would more likely buy from the same salesperson during a repeat visit.

Data Collection and Measures

The sample consists of repeated measures from 1,470 salespeople at 209 stores over two years, one year before and one year after the training. Of these stores, 21 stores containing 162 salespeople did not send any of their crew to the training event (control condition), 58 stores with 361 salespeople trained everyone (full condition), and 130 stores with 947 salespeople trained a subset of their salespeople (partial condition). The average size of store sales force was 7.03 (SD = 1.10), ranging from 4 to 9 salespeople per store. Partial stores had sent on average 3.70 (SD = 1.16; Min = 2 Max = 6) salespeople to training which represented an average of 51.25 % (SD = 16.18%; Min = 22.22% Max = 75.00%) of their entire sales force.

The data provided me with an objective measure of pre- and post-training store sales defined as actual sales divided by the square footage of the store (sales per square feet). Other covariates included conversion rate (defined as the yearly rate of the number of people who purchase something divided by the number of people who enter the store), store traffic count and average transaction value (yearly rates), manager’s tenure (in months), age and education (in years). The breakdown of descriptive statistics of store-level measures to each condition is presented in Table 1.1. To ensure that I compare same stores that only randomly differ from one another I matched stores in the three conditions on selected covariates using a matching method called marginal mean weighting with propensity score stratification (MMP-S) that I describe later on in the paper.

TABLE 1.1
Descriptive Statistics of Stores Prior to Matching

Variables	**T_0=Control**		**T_1=Partial**		**T_2=Full**		**Total**	
n	*n=21*		*n=130*		*n=58*		*n=209*	
# of salespeople	7.71	(.71)	7.28	(.70)	6.22	(1.47)	7.03	(1.10)
Pre-training sales/sq. ft.	1031.76	(86.04)	1162.1	(142.50)	1368.05	(224.00)	1206.2	(196.57)
Average transaction value	108.9	(8.87)	124.63	(15.42)	146.01	(26.17)	128.99	(21.82)
Conversion rate	47.76	(3.34)	54.03	(6.22)	62.98	(10.12)	55.88	(8.72)
Store traffic	82.14	(12.33)	99.99	(13.88)	115.83	(15.79)	102.59	(17.25)
Manager’s age	50.57	(14.09)	49.14	(12.21)	46.71	(11.17)	48.60	(12.14)
Manager’s education	2.76	(.77)	3.05	(.66)	3.21	(.77)	3.06	(,71)
Manager’s tenure	74.19	(54.88)	70.10	(46.18)	62.55	(41.87)	68.41	(45.90)
Manager’s income	58956	(2921)	62506	(4140)	69262	(7494)	64024	(6206)
Performance diversity	.25	(.02)	.25	(.09)	.18	(.08)	.24	(.09)
Post-training sales/sq. ft.	960.14	(81.87)	1222.1	(243.26)	1648.84	(406.34)	1314.2	(363.00)
Change in sales/sq. ft.	-71.61	(107.59)	59.95	(172.82)	280.81	(241.80)	108.02	220.65

Salesperson’s behavior was a post-training measure defined as the proportion of the total customers a salesperson had sold to throughout the year for whom she had used personalized, relationship-enhancing messages. The performance measure was provided as the actual sales divided by a desired level of sales through the year before and after the training. Other variables included salespeople’s demographics (age, tenure, income, full-time or part-time), number of documented employee referrals that were hired by the retailer, salesperson’s spending on branded gift as well as non-gift merchandise, their self-reported perceptions of the brand’s quality, prestige, distinctiveness, and mystique and their commitment to and identification with the store.

I measured individual-level variables mostly for my micro analysis in partial stores to see the moderating factors in training spillover from trained to untrained salespeople. Moreover, there are certain variables that can only be defined for partial stores (e.g. tenure diversity of the trained group). Thus to save space, I only provide means, standard deviations and the inter-correlation matrix of variables for salespeople in partial stores to be consistent with my individual-level analysis. Table 1.2 summarizes the descriptive statistics of this data. Descriptive statistics for individual variables in control and full-training conditions are also available upon request. Also to save further space, I present the breakdown of individual covariates between trained and untrained salespeople in partial stores in appendix where I analyze balance of pre-training covariates between trained and untrained salespeople before and after using a matching method.

To capture group diversity, I used the coefficient of variation (COV; the standard deviation divided by the mean) which is established as the most reliable and scale-invariant measure of dispersion (O'Reilly, Caldwell, and Barnett 1989) and has been used in most of the research studying group cohesion (Harrison, Price, and Bell 1998; Jackson et al. 1991; O'Reilly, Caldwell, and Barnett 1989). I applied this measure to individual performances to capture performance diversity in a store. To obtain tenure diversity of the trained group, I used COV of tenure for the trained salespeople in partial stores.

In contrast to these two store-level diversity measures, performance dissimilarity to the trained group is an individual variable depicting the distance of a given salesperson's performance from the group of the trained peers. To attain this, I used a Euclidean distance measure widely used in the literature (Jehn, Rispens, and Thatcher 2010; O'Reilly, Caldwell, and Barnett 1989; Riordan and Wayne 2008; Tsui, Egan, and O'Reilly 1992) and defined as $(\sum_{j=1}(p_i - p_j)^2/n)^{1/2}$ where p_i is the performance of the focal salesperson, p_j is the performance of the j^{th} salesperson in the trained group and n is the number of the trained salespeople in that partial store.

Methodological Challenges

In my field experiment, stores are assigned to one of the following three treatment levels: the control condition (T_0), the partial condition (T_1), and the full condition (T_2).

TABLE 1.2
Intercorrelation Matrix for Covariates in Partial Stores

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1.PERF	1																											
2.PERZ	.74**	1																										
3.ΔPRF	-.24**	.42**	1																									
4.AGE	-.03	-.05	-.05	1																								
5.TEN	-.01	-.02	-.05	.07*	1																							
6.INC	-.01	-.03	-.06	-.00	-.01	1																						
7.FUL	-.01	-.02	.01	-.00	-.01	-.01	1																					
8.ID	.21**	.25**	.15**	-.01	-.04	-.02	-.04	1																				
9.BNF	-.01	.00	-.01	.01	-.02	-.05	.01	-.01	1																			
10.REF	.25**	.30**	.17**	-.02	-.02	-.03	-.04	.70**	-.03	1																		
11.SPD	.21**	.17**	-.04	.00	.01	-.04	-.07*	.40**	-.01	.58**	1																	
12.GIF	.20**	.23**	.22**	.00	-.02	.04	-.03	.53**	-.01	.66**	.40**	1																
13.NOR	.18**	.23**	.21**	-.02	-.03	-.02	-.01	.46**	.02	.57**	.35**	.48**	1															
14.AFF	.25**	.28**	.13**	.91**	.23	.19	-.94**	.48**	-.05	.61**	.37**	.48**	.42**	1														
15.CON	.18**	.21**	.14**	.00	-.26	.15	-.44	.51**	-.33	.61**	.37**	.50**	.47**	.42**	1													
16.VAL	.23**	.26**	.15**	-.02	.01	-.01	00	.52**	-.01	.63**	.39**	.53**	.42**	.47**	.47**	1												
17.PRG	.21**	.28**	.20**	-.01	00	-.03	-.07*	.57**	-.02	.69**	.43**	.56**	.50**	.48**	.48**	.53**	1											
18.MYS	.20**	.25**	.15**	-.00	-.06*	-.02	-.11**	.60**	.01	.70**	.44**	.56**	.46**	.48**	.50**	.54**	.55**	1										
19.DIST	.24**	.27**	.14**	.03	-.03	-.03	-.06	.60**	-.00	.72**	.44**	.55**	.45**	.50**	.50**	.55**	.57**	.60**	1									
20.TRF	.14**	.20**	.08	-.05	.04	-.03	-.04	.32**	.01	.41**	.22**	.32**	.27**	.32**	.29**	.32**	.34**	.33**	.35**	1								
21.SPSF	.12**	.16**	.05	-.05	.03	-.03	-.04	.25**	.03	.34**	.22**	.27**	.23**	.27**	.25**	.29**	.30**	.28**	.26**	.59**	1							
22.ATV	.17**	.20**	.05	-.03	.02	-.05	-.03	.31**	.03	.40**	.23**	.34**	.26**	.29**	.30**	.32**	.31**	.33**	.34**	.68**	.68**	1						
23.CVR	.17**	.17**	-.00	-.04	.04	-.06	-.02	.27**	.01	.33**	.24**	.26**	.22**	.23**	.28**	.29**	.28**	.28**	.28**	.61**	.65**	.7**	1					
24.SAG	.02	.05	.03	.00	.05	.03	.03	.06	-.01	.04	.01	.04	.05	.07*	.04	.04	.08*	.01	.06*	.11**	.07*	.06^	.05	1				
25.SED	.02	-.02	-.03	-.01	-.07*	.06	.02	-.03	.01	-.03	-.01	-.04	-.05	-.03	-.02	-.06*	-.04	-.03	-.03	-.12**	-.03	-.15**	-.16**	.00	1			
26.STE	-.02	.02	.05	.04	.03	-.01	-.02	.06	-.05	,03	-.01	.04	.04	.06	.02	.05	.05	.02	.03	.09**	.13**	.14**	.05	.44**	-.2**	1		
27.PD	-.21**	-.23**	-.13**	.03	.01	-.04	.01	-.10**	-.03	-.14**	-.06*	-.10**	-.12**	-.08*	-.09**	-.05	-.10**	-.11**	-.12**	-.20**	-.10**	-.18**	-.07*	.06*	-.09**	.10**	1	
28.TDt	-.02	-.04	.08	.01	-.07*	-.00	.04	-.02	.02	-.03	-.01	.02	.01	.04	-.06	.01	-.02	-.02	-.02	-.06	.06	-.01	-.04	-.03	.04	-.04	.11**	1
M	.80	.56	.07	37.76	38.70	33740	.52	3.87	2.00	2.74	494	238	4.26	3.90	3.88	3.89	3.94	3.89	4.00	99.7	1159	124	53.94	49.04	3.06	69.95	.26	.38
SD	.22	.21	.15	7.35	15.19	7208	.50	2.05	.70	1.90	355	131	1.78	1.95	1.98	1.96	2.03	2.01	2.01	14	141.9	15.46	6.13	12.16	.66	46.02	.09	.16

*$p < .10$ **$p < .05$

Notes: PERF = Pre-training performance, PERZ=personalization, ΔPRF=performance change, AGE=salesperson's age, TEN=salesperson's tenure, INC=salesperson's income, FUL= binary variable with full-time as 1 and part-time as 0, ID= identification, BNF=salesperson's benefit level, REF=referrals, SPD= salesperson's spending on branded merchandise, GIF= salesperson spending on branded merchandise for gifts, NOR=normative commitment, AFF=affective commitment, CON=continuance commitment, VAL=perceived brand value, PRG=perceived brand prestige, MYS=perceived brand mystique, DIST=perceived brand distinctiveness, TRF=store traffic, SPSF=pre-training sales per sq. ft., ATV=store's average transaction value, CVR=store's conversion rate, SAG=store manager's age, SED=store manager's education, STE=store manager's tenure, PD=store's prior performance diversity, TDt=tenure diversity of the trained group.

Also, within the partial stores, salespeople are assigned to either the training (t_1) or the control (t_0) condition. To make my field experiment as close to a randomized lab experiment as possible, I have to account for a priori differences that might lead to a selection bias. Randomized experiments guarantee that the treated and the control units are only randomly different from one another on all important pre-treatment background covariates. Ignoring a priori dissimilarities leads to selection of a treatment and a control group that are systematically different from the very beginning, which biases any inference based on their post-treatment differences.

As a remedy, matching and weighting methods based on propensity scores (Rosenbaum and Rubin 1983) have increased in popularity and complexity among researchers dealing with observational (non-randomized) data across various disciplines such as political science (Ho et al. 2007), education (Hong and Raudenbush 2006), sociology (Morgan and Harding 2006), economics (Imbens 2004), psychology (Harder, Stuart, and Anthony 2010), and statistics (Rubin 2006). These methods aim to create treatment and control groups that look only randomly different from one another on confounding covariates, and hence are comparable (Stuart 2010).

Simply controlling for confounding covariates does not alleviate selection bias in field experiments and even creates further bias (Ho et al. 2007; Messer, Oakes, and Mason 2010). Especially when the treated and control groups have different distributions of covariates, controlling for covariates leads to extrapolation to unmatched areas where control units are accompanied by treatment units or vice versa. This makes the direction of causality extremely sensitive to minor modifications in the model (Ho et al. 2007; King and Zeng 2007). By deleting or weighting the unmatched observations, matching methods ensure that treated and control units were similar to each other before the treatment was applied.

Besides the selection bias, my data poses two additional challenges. First, while most matching methods are designed for two-level treatment variables (i.e. treatment vs. control), my store-level analysis contains three levels (i.e. control vs. partial vs. full). Also my store sample size does not allow me to freely delete unmatched observations. To attenuate this problem I utilize a recently developed method called marginal mean weighting through propensity score stratification (MMW; Hong 2012; Hong 2010)that is superior to similar weighting methods (e.g. inverse probability weighting; IPW) and can be applied to multi-treatment analyses (Hong 2012; Hong and Hong 2009). In this method, for each treatment level the sample is stratified into various groups where in each group observations receiving that treatment have similar covariate distributions with others. Observations are then weighted based on the stratum they fall in and computed weights are used in subsequent statistical analyses. I explain the procedure in more detail in my results section.

The second challenge I face pertains to the stable unit treatment assumption (SUTVA) of causal analysis (Rubin 1978). Under SUTVA, a salesperson's outcome is independent of whether his/her peer has received the training. Quite the contrary, in this research I are interested in the spillover effect of training on untrained salespeople. To relax this assumption and test my spillover hypothesis I compare untrained salespeople in partial stores with salespeople in the control group to measure the effect of being in a partial store versus a control store on performance change of untrained salespeople. I use store weights computed in my store-level analysis to ensure that the only difference between the stores in which these untrained salespeople are compared with each other is that some of these stores used partial training. Salespeople did not differ significantly on key covariates. Moreover I use multilevel modeling (Raudenbush and Bryk 2002) to include other store-specific factors that might also influence the outcomes.

Empirical Strategy

The analysis includes two broad stages: a macro (store-level) and a micro (salesperson-level) analysis. The store-level analysis investigates whether partial-training can be as effective as full-training when the diversity of performance is low. Hence the change in store sales per square foot is compared across the three training policies, control, partial-, and full-training and MMW-S method is used to balance stores across these conditions. I also focus on store observations in the partial condition and test the moderating role of tenure diversity of the trained group.

The next step investigates the spillover effect of training. The spillover effect is significant if having vs. not having trained peers in the store significantly enhances performance of the untrained salespeople. Hence the spillover analysis is carried out on the untrained salespeople in partial stores plus salespeople in control stores to check the significance of the store-level treatment variable, T_1, which captures whether salespeople are in a partial store or a control store. Store weights calculated in the store-level analysis are used to make sure that pre-training characteristics of the stores did not affect the training policy they chose. The moderating effect of performance diversity is also tested here. In the third step, I need to focus on individual salespeople within the partial stores to test my individual hypotheses. A multilevel propensity score matching method ensures that trained and untrained salespeople were similar people before some of them were sent to the training. To dig even deeper, in my final analysis I look at the total group (unmatched) of untrained salespeople in partial stores to see if individual similarity to the trained group in performance can partly explain the spillover effect.

ANALYSIS AND RESULTS

Store-Level Analysis

Before I match stores in the three conditions to ensure that they were similar prior to training, I had to choose which covariates to include in the matching procedure. Since the selection process is not known, the selected covariates should theoretically or empirically influence treatment selection, and/or conditional on the treatment affect the outcome (Austin 2011). Moreover, because the dependent variable is change in store sales, the most natural covariate to include is pre-training sales of each of the stores. Also the covariates should entail the difference between general profiles of the stores. To better decide on the covariates to match on, I ran a multinomial logit model with T_i as my dependent variable and store-level variables as covariates. The results show that full and partial training stores had more traffic, were more successful in converting sales, and had younger managers with higher education levels.

The recently developed method of MMW-S (Hong 2012) is applied in disciplines such as education and epidemiology (Hong and Hong 2009; Hong and Raudenbush 2006) and is extremely well-suited for multi-treatment analyses involving selection bias (Hong 2012). I used the following three steps to match the stores with MMW-S.

First, for each $T_{i\ I}$ ran a binary logistic model to determine the probability that T_i is chosen over the other two conditions, given the covariates. Next, I stratified the whole sample into different strata based on the fitted values of the logistic model (i.e. propensity score) such that in each stratum, the relevant covariates as well as the propensity score had the same distribution for those observations that received that treatment and those which did not. For instance Table 1.3 shows the stratification for T_1=partial training and the means for the propensity score and pretreatment store sales.

TABLE 1.3
Balance for the Propensity Score and Sales/Sq Ft for Partial Stores

	Partial Training (T_2 = 1)			**Others (T_2 = 0)**		
Stratum	n	M_{PS}	M_{SPSF}	n	M_{PS}	M_{SPSF}
1	22	.4234	1306.54	38	.3524	1455.76
2	21	.5824	1190.38	18	.5802	1174.38
3	22	.6639	1199.81	5	.6639	1069.80
4	21	.7366	1108.23	5	.7408	1056.20
5	22	.8051	1106.09	10	.8010	1077.90
6	22	.8714	1060.77	3	. 8761	1049.00
Total	130	.6808	1162.16	79	.6692	1147.66

% of balance improvement in mean difference across Subclasses

Propensity score	92.54%
Pre-training sales per sq. ft.	87.55%

Notes: M_{PS} = mean of the logit of the propensity score, M_{SPSF} = mean of pre-training sales per sq. ft.

For example Table 1.3 shows that in the second stratum 21 partial and 18 other stores exist and the mean of the propensity score and other covariates such as pretreatment sales is closely matched. There is no right number of strata and I stratified the sample to the point that I got the best balance between the covariates. Figure A1 in the Appendix summarizes covariate balance measured as standardized mean difference between treatment and control group for T_1 = partial stores and T_2 = full stores across all strata.

As the final step, stores in treatment group T_i and stratum S receive marginal mean weights computed as MMW = $(n_S/n_{Ti,S}) \times \text{prob}[(T_i) = 1]$ where n_S is the number of stores in stratum S, $n_{Ti,S}$ is the number of stores in stratum S that are assigned to treatment T_i, and prob[(T_i) = 1] is the overall proportion of the stores in treatment group T_i. Table 1.4 presents the complete stratification information with computed marginal mean weights. As an example, partial training stores in stratum 3 receive a weight of (52/15) × (58/209) = .96. I used computed marginal mean weights as regression weights in my subsequent store-level analysis.

TABLE 1.4
Marginal Mean Weights and the Distribution of Observations across the Strata

	T_0 = Control Stores				**T_1 = Partial Training**				**T_2 = Full Training**			
Str.	MMW	T_0=1	T_0=0	Total	MMW	T_1=1	T_1=0	Total	MMW	T_2=1	T_2=0	Total
1	2.38	7	159	166	1.69	22	38	60	7.21	2	50	52
2	.44	7	24	31	1.15	21	18	39	4.81	3	49	52
3	.17	7	5	12	.79	22	5	27	.96	15	37	52
4	-	-	-	-	.77	21	5	26	.39	38	15	53
5	-	-	-	-	.90	22	10	32	-	-	-	-
6	-	-	-	-	.70	22	3	25	-	-	-	-
Total				209				209				209

Note: MMW = Marginal Mean Weights.

Before running a more detailed spotlight analysis on the moderating role of performance diversity, a median split of the diversity measure is presented to better visualize the differences between the three conditions. Figure 1a shows the results of a weighted ANOVA with MMW as regression weights and change in store sales as the dependent variable. The 3 (control vs. partial vs. full training) × 2 (high performance diversity vs. low performance diversity) between subjects weighted ANOVA reveals significant difference between the three store training policies ($F(2, 203) = 10.24$, $p < .0001$, $\eta^2 = .09$).

I used coding suggestions made in the web Appendix of Spiller et al. (2013) for spotlight analysis with a 3-level model and regressed the change is store’s sales per square feet on the mean-centered performance diversity (COVPERF), T_0 (no-training), T_2

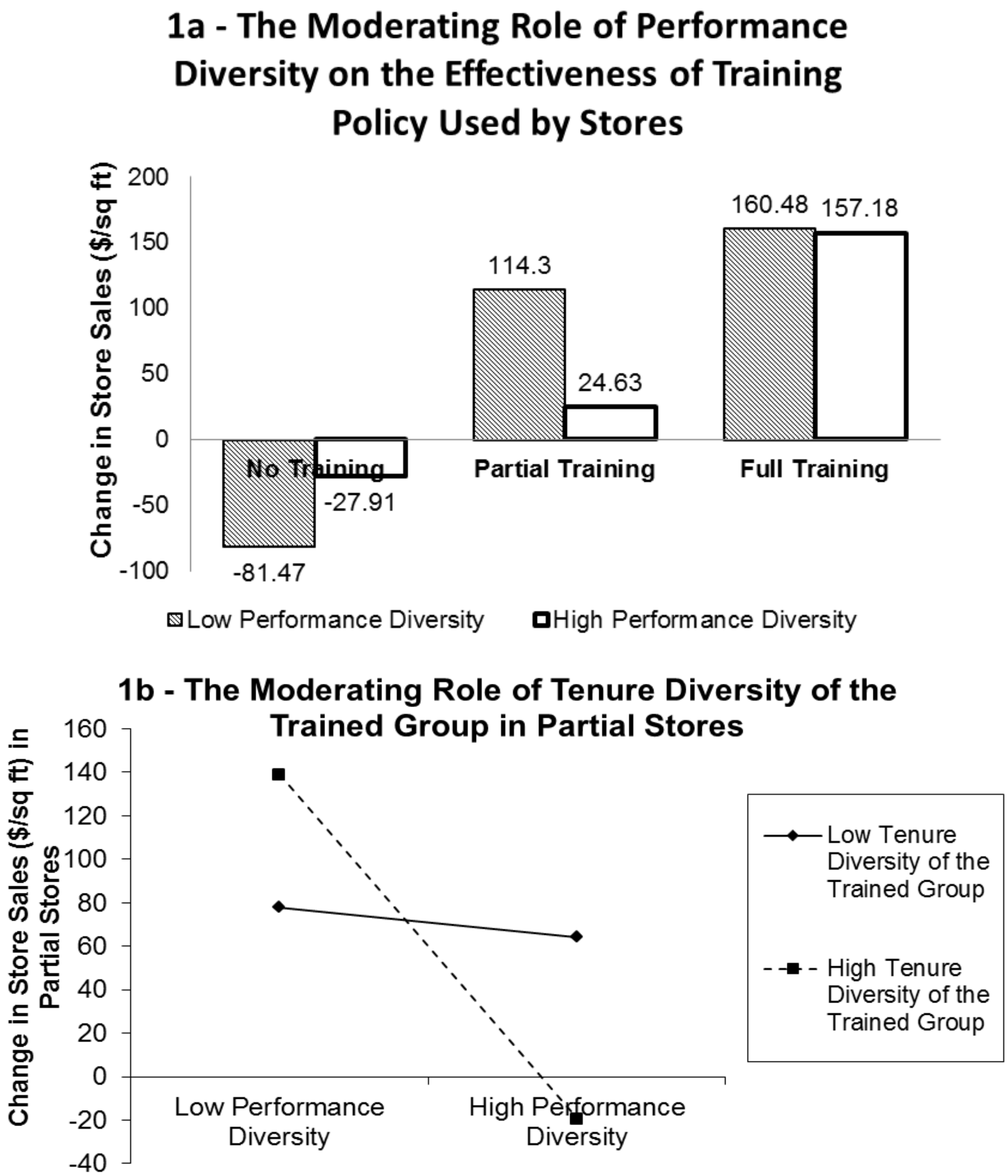

FIGURE 1.1 – Change in Store Outcomes Due To Training Policies

(full-training), and the interaction terms with MMW as regression weights. This regression revealed a marginally significant interaction between T_2 and COVPERF (β =

.14, t = 1.77, p = .07) indicating the difference in the slope of COVPERF between full-training and partial-training.

A spotlight analysis at one-SD below the mean of COVPERF revealed that in less diverse stores, the difference between fully-trained and partially-trained stores was not significant (β_{T2} = .06, t = .67, p = .50), while the difference between the control stores vs. the partially-trained was significant (β_{T0} = -.27, t = - 2.18, $p < .05$). A similar spotlight analysis at one-SD above the mean of COVPERF showed a significant difference such that in diverse stores, sales had a higher jump when everyone was trained compared to when part of the salesforce were trained (β_{T2} = .35, t = 3.02, $p < .01$), while the difference between the control stores vs. the partially-trained was not significant (β_{T0} = -.11, t = -1.31, p = .19). These results further corroborate H_{1a} that partial training is as effective as full training when store salespeople have close performance levels.

Next I focused on partial stores and ran a weighted regression model with store change in sales as the DV and MMW as regression weights. Table 1.5 demonstrates the results of this regression. Figure 1b shows the interaction between performance diversity and tenure diversity of the trained, supporting H_{4a}.

TABLE 1.5
WLS Analysis of the Moderating Effects of Diversity Measures on Change of Sales/Sq.Ft. in Partial Stores

Dependent Variable
Change in SPSF

	B	S.E.
Intercept	**74.69***	(14.60)
SPSF_PRE	**.199***	(.1)
PD	**-466.34***	(154.48)
TDt	12.94	(90.67)
PD × TDt	**-2368.56***	(880.13)
R^2	.156	
Adjusted R^2	.129	
$\Delta F(4, 125)$	**5.78***	

*$p < .05$; *Notes*: SPSF = Store sales per square feet, SPSF_PRE = Store sales per square feet 12 months prior to study, PD = Performance Diversity of the store, TDt = Tenure Diversity of the Trained Group.

Although the pattern of changes in store sales follows my hypotheses, the presented results are based on aggregate, store-level analysis and might not reflect the true individual pattern of information spillover among trained and untrained salespeople. In the following sections I took a more micro look at the spillover of training.

The Spillover Effect

To establish that training spills over from the trained to the untrained salespeople, I must demonstrate that the untrained salespeople in partial stores have higher performance increases than salespeople in control stores. Hence for the untrained salespeople, the spillover effect is the effect of being in a partial store versus being in a control store. Since a priori differences in stores might affect the policy they chose, I used MMW computed in the previous section to have comparable control and partial stores. Since my data has a multilevel structure with salespeople nested within stores, I ran the following weighted multilevel model on the trained salespeople with MMW as regression weights:

$$\Delta PERF_{ij} = \gamma_{00} + \gamma_{01}PARTIAL_j + \gamma_{02}PD_j + \gamma_{03}PD_j \times PARTIAL_j + \gamma_{10}PERF_{ij} + u_{0j} + r_{ij} \quad (1)$$

where $\Delta PERF_{ij}$ = performance change of salesperson i within store j, PERF = salesperson's pre-training performance, PARTIAL = binary variable with partial stores as 1 and control as 0, PD = pre-training performance diversity of the store, u_{0j} = store-level random shock, and r_{ij} = individual-level error (see Table 1.6). The results support H3a and H3b, as depicted in Figure 1.2.

Individual-Level Analysis

My results up to this point have supported my hypotheses from a macro perspective. However, unless I specifically analyze trained and untrained salespeople's

TABLE 6
The Spillover Effect of Training

Dependent Variable *Performance Change*	**Model 0** (Intercept Only)		**Model 1** (Fixed Effects)		**Model 2** (with Interactions)	
Fixed Effects	γ	S.E.	γ	S.E.	γ	S.E.
Intercept	**0.06***	(.01)	-.01	(.01)	-.01	(.02)
Prior performance			**-.36***	(.03)	**-.38***	(.03)
PD			**-.45***	(.1)	.44	(.23)
PARTIAL			**.09***	(.02)	**.09***	(.02)
PARTIAL × PD					**-1.03***	(.25)
Error Variance						
Residual	.01*	(.001)	.013*	(.0009)	.013*	(.0009)
Level-2 Intercept	.009*	(.001)	.007*	(.001)	.005*	(.001)
Model Fit						
-2 Restricted Log-Likelihood	-483.4		-580.6		-594.4	
AIC	-479.4		-576.6		-590.4	
BIC	-473.3		-570.6		-584.4	

*p < .05; Intra-class correlation coefficient (ICC) = .47
Notes: PARTIAL = A binary variable with 1 if the store was a partial store, PD=Performance Diversity of the Store.

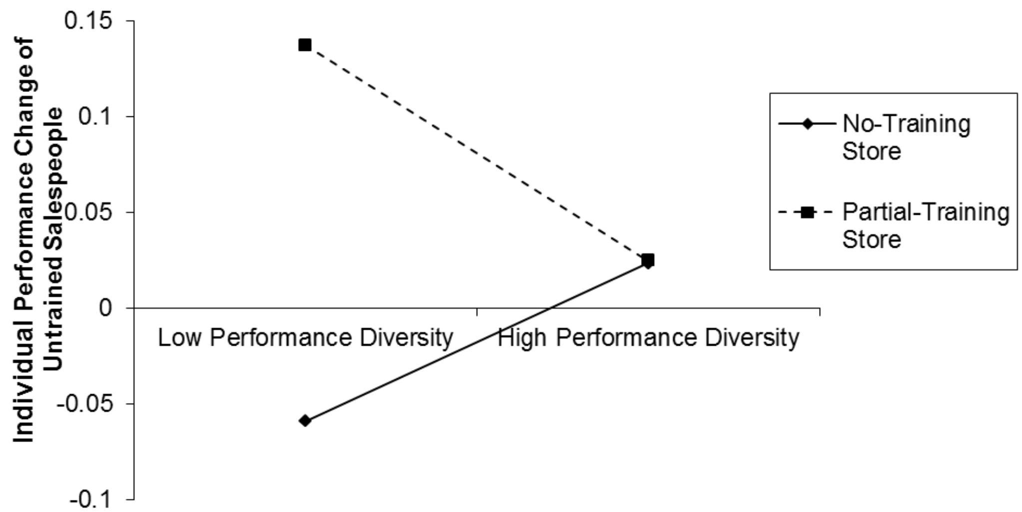

FIGURE 1.2 – The Spillover Effect of Training

behavior in partial stores I cannot ascertain whether my store-level results were actually demonstrating training spillover. To do this I have to first match trained and untrained salespeople based on relevant pre-training covariates.

I ran a multilevel propensity score matching method in which the propensity scores are the fitted values from a 2-level logistic regression of probability of receiving the training on 19 individual- and 7 store-level covariates. The algorithm then matches treatment and control salespeople which have the closest propensity scores and covariate distributions, a method called nearest neighbor matching (Stuart 2010). The matched sample includes 253 untrained and 341 trained salespeople. Table A.1 and Figure A.2 in appendix give detailed report and graphics of the balance of covariates for trained and untrained salespeople before and after matching.

So far I had only assumed that the training was effective. To test this assumption I ran a difference in difference test on the matched salespeople. The results demonstrated in Table 1.7 show that although trained and untrained salespeople were similar people before the training (since they are matched on about 30 relevant covariates), the training made a difference for those who received it, but not for those who did not (on average).

TABLE 1.7
Difference-In-Differences for Performance Change of Matched Salespeople in Partial Stores

	Pre-Training Performance	Post-Training Performance	*Difference (Post-Pre)*
Trained	.895	1.079	.184*
	(.008)	(.013)	(.010)
Untrained	.890	.836	-.054
	(.010)	(.015)	(.012)
Difference (Trained-Untrained)	.005	.243*	.238*
	(.013)	(.020)	(.016)

*$p < .05$; standard errors are in parentheses.

I also compared trained and untrained salespeople by looking at the behavior. I found that a trained salesperson sends personalized messages to a significantly higher proportion of their customers than the untrained salespeople ($M_{trained}$ = .71, SD = .13, $M_{untrained}$ = .43, SD = .13, t(592) = -25.27, p < .0001).

I ran the following multilevel model on the individual data in partial stores:

$$PERSLZ_{ij} = \beta_{0j} + \beta_{1j}PS_{ij} + \beta_{2j}training_{ij} + r_{ij} \ (2)$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}PD_j + \gamma_{02}TDt_j + u_{0j} \ (3)$$

$$\beta_{1j} = \gamma_{10}, \beta_{2j} = \gamma_{20} + \gamma_{21}PD_j + \gamma_{22}TDt_j + u_{1j} \ (4)$$

where $PERSLZ_{ij}$ =the behavior measure (personalized messages) for salesperson i in store j, PS= the logit of the propensity score, training = binary variable with 1 for trained and 0 for untrained salespeople, PD = performance diversity, TDt = tenure diversity of the trained group. Table 1.8 summarizes the results of this analysis. Consistent with my previous results, I find a significant negative main effect of performance diversity in partial stores. Of special interest are the differing effects of performance diversity and tenure diversity of the trained group on the behavior of trained and untrained salespeople. Figures 3a and 3b illustrate these moderating effects, demonstrating support for H1b and H4b.

To further show that the type of the behavior is the main indicator of performance change, I ran another multilevel analysis, once with PERSLZ excluded and once included. I find that the effect of training on performance change becomes insignificant when PERSLZ is included in the model, suggesting that the behavior is the main reason why performance goes up. Table 1.9 summarizes the results.

TABLE 1.8
Weighted HLM Analysis of the Effect of Training on Matched Salespeople's Behavior in Partial Stores

Dependent Variable *Personalized Messages*	**Model 0** (Intercept Only)		**Model 1** (Fixed Effects)		**Model 2** (with Random Slope of Training)		**Model 3** (with Cross-Level Interactions)	
Fixed Effects	γ	S.E.	γ	S.E.	Γ	S.E.	Γ	S.E.
Intercept	**.62***	(.01)	**.32***	(.01)	**.31***	(.02)	**.31***	(.02)
Logit of propensity score			**.17***	(.02)	**.22***	(.02)	**.22***	(.02)
Training			**.27***	(.01)	**.25***	(.02)	**.25***	(.01)
PD			**-.16***	(.08)	-.02	(.07)	**-.66***	(.15)
TDt			**-.14***	(.04)	**-.18***	(.04)	**.30***	(.09)
Training × PD							**.80***	(.18)
Training × TDt							**-.61***	(.10)
Error Variance								
Residual	.020*	(.001)	.01*	(.007)	.005*	(.0004)	.005*	(.001)
Level-2 Intercept	.007*	(.001)	.004*	(.008)	.02*	(.003)	.01*	(.002)
Training					.03*	(.005)	.01*	(.003)
Model Fit								
-2 RLL	-346.08		-803.59		-1001.02		-1037.71	
AIC	-342.08		-799.59		-993.02		-1029.71	
BIC	-333.4		-790.93		-975.69		-1012.39	

*p < .05; Intra-class correlation coefficient (ICC) = .26
Notes: PD = Performance Diversity of the store, TDt = Tenure Diversity of the Trained Group.

TABLE 1.9
Weighted HLM Analysis of The Effect of Personalized Messages on Matched Salespeople's Performance Change in Partial Stores

Dependent Variable *Performance Change*	**Model 0** (Intercept Only)		**Model 1** (without PERSONALIZE)		**Model 3** (with PERSONALIZE)	
Fixed Effects	γ	S.E.	γ	S.E.	γ	S.E.
Intercept	**.11***	(.01)	**-.15***	(.06)	**-.38***	(.04)
Logit of propensity score			-.08	(.06)	**-.11 ***	(.04)
Training			**.21***	(.01)	-.03	(.01)
PERSONALIZE					**.89***	(.05)
Pre-training performance			**.27***	(.09)	.03	(.07)
Error Variance						
Residual	.031*	(.002)	.02*	(.001)	.013*	(.001)
Level-2 Intercept	.013*	(.002)	.008*	(.001)	.005*	(.001)
Model Fit						
-2RLL	-227.61		-399.69		-666.05	
AIC	-223.61		-395.69		-662.05	
BIC	-214.94		-387.03		-653.39	

*p < .05; Intra-class correlation coefficient (ICC) = .29
Notes: PERSONALIZE = Proportion of a salesperson's customers for whome personalized messaging is used.

Finally, I ran a model only on the untrained salespeople in partial stores including untrained salespeople that were deleted from my matching procedure to allow for dissimilarity variation. Consistent with my previous results I find that individual similarity in performance to the trained group increases the untrained salespeople's use of personalized messages, thus supporting H2. Also this effect gets amplified when the diversity of the trained group is higher, supporting H4c (Table 1.10 and Figure 1.3, panel 3c).

TABLE 1.10
HLM Analysis of the Effect of Similarity of Untrained Salespeople in Prior Performance to the Trained Group on the Untrained's Behavior

Dependent Variable *Personalized Messages (Used by Untrained Salespeople)*	**Model 0** (Intercept Only)		**Model 1** (Fixed Effects)		**Model 2** (with Interactions)	
Fixed Effects	γ	S.E.	γ	S.E.	Γ	S.E.
Intercept	**.39***	(.01)	**.42***	(.01)	**.42***	(.01)
Logit of propensity score			-.007	(.03)	-.004	(.03)
Pt			**-.35***	(.05)	**-.35***	(.05)
Tt			-.0003	(.005)	-.0003	(.005)
PD			**-.46***	(.08)	**-.44***	(.08)
TDt			**-.20***	(.04)	**.25***	(.04)
Pt × PD					-.09	(.33)
Pt × TDt					**-.43***	(.19)
PD × TDt					-.03	(.45)
Error Variance						
Residual	.009*	(.001)	.01*	(.0007)	.007*	(.001)
Level-2 Intercept	.009*	(.001)	.002*	(.0006)	.002*	(.001)
Model Fit						
-2 Restricted Log-Likelihood	-652.73		-830.73		-836.73	
AIC	-648.73		-826.73		-832.73	
BIC	-640.45		-818.48		-824.49	

*$p < .05$; Intra-class correlation coefficient (ICC) = .49
Notes: Pt = Untrained Salesperson's Prior Performance Dissimilarity to the Trained Group, Tt = Untrained Salesperson's Tenure Dissimilarity to the Trained Group, PD=Performance Diversity of the Store, TDt=Tenure Diversity of the Trained Group.

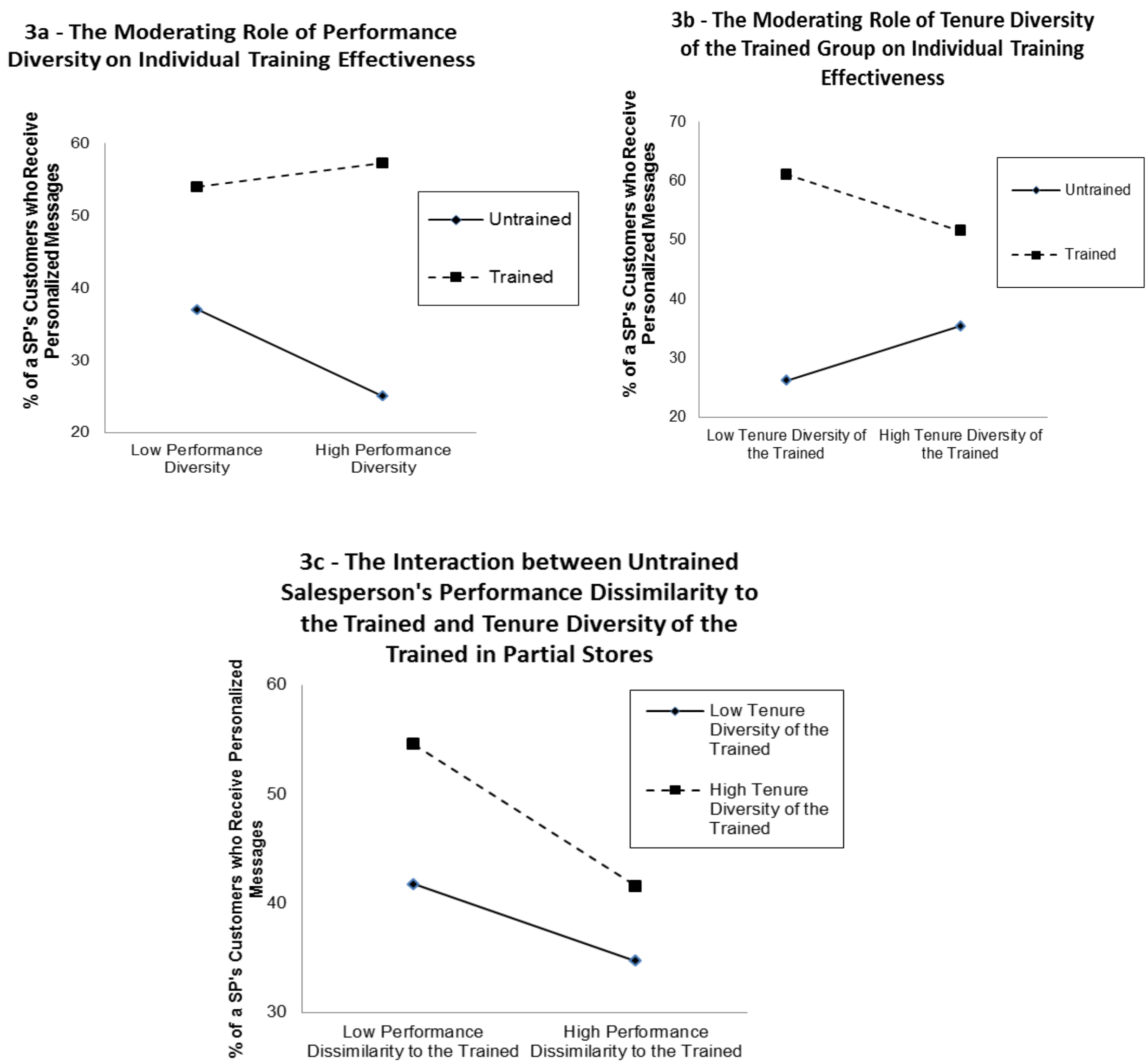

FIGURE 1.3 – Moderating Roles of Diversity and Similarity in Partial Stores

GENERAL DISCUSSION

Despite the prevalence of sales training programs and the substantial expenditures necessary to support such efforts, little effort has been given to understanding the potential for knowledge spillover among salespeople from those who receive training to those who do not. Moreover, understanding the efficacy of training a subset of the sales team versus the entire sales team can provide important cost-saving insights for managers. In an effort to address this gap in knowledge, I investigate macro-level conditions of the retail-unit in which training a subset of the sales team results in similar performance changes to training all salespeople. Additionally, at the micro-level, I investigate characteristics of trained salespeople that are most likely to result in knowledge spillover to untrained salespeople, and ultimately to enhance store-level performance.

To my knowledge, this research is the first to examine the comparative effects of training all versus a subset of all salespeople. As such, my study reveals valuable insights that managers can use to help determine which stores should engage in full- versus-partial training, as well as choosing which groups of salespeople to train within a retail unit. I find that partially-trained stores with low performance diversity can have similar outcomes as fully-trained stores. Also, the spillover is enhanced when the group of trained salespeople is diverse in tenure. my more granular analysis on the individuals within the control and the partially-trained stores corroborates my macro findings on the stores. Moreover I find that spillover is more driven by similarity in performance, which attests to the fact that close rivals mimic each other. Thus, my results offer clear, actionable strategies to managers in deciding when to choose partial training and which salespeople should receive training.

In line with previous research on self-efficacy (e.g. Bandura 1986), the anticipated outcome of sales training is increased competence among those receiving the training, which should translate to increased sales performance. Therefore, it is not surprising that within my study, those stores where everyone is trained appear to have the highest boost in sales in both high and low performance diversity conditions. This advantage can be attributed to the enhanced competence and resulting performance of the trained group in these stores. However, the moderating influence of performance diversity is particularly interesting when considering partial-training stores. Specifically, the difference in performance change between partial-training stores and no-training stores is greatest when performance diversity of the sales team is low and marginal when performance diversity is high. Consistent with my theorizing, because training is less likely to spillover to the rest of the sales crew in diverse stores, the entire sales force in such partially-trained stores fail to perform at a similar level to salespeople in full-training stores. However, performance changes in partial stores with low performance diversity approach those of full-training stores. Interestingly, performance change among control groups seems to decrease over the course of the study. I speculate that this is because my data was gathered in the early years of the economic crisis when most retailers lost profits. Because the training emphasized forging relationships with existing customers, stores that implemented even partial-training avoided losses by enticing past customers return to stores.

In-group commonalities can result from a number of demographic characteristics, of which tenure is most frequently examined due to its significant influence on group processes (O'Reilly, Caldwell, and Barnett 1989). Moreover, tenure diversity tends to be quite salient among groups of salespeople where less variation in other demographic variables is observed, and the resulting in-group/out-group distinction helps dictate the behaviors of individual salespeople. Typically, working in a homogeneous group (i.e., similar age and starting date) is attractive to employees, as individuals within an in-group often share similar experiences and a common perspective as well as sharing information with each other (Mesmer-Magnus and DeChurch 2009; Tsui and O’Reilly III 1989). However, this also implies, then, that those within a homogenous group are less likely to share information with the out-group when strong in-group/out-group distinctions exist. Thus, given that low tenure diversity (i.e., homogeneity) serves to facilitate in-group categorizations, thereby minimizing the likelihood of sharing information with out-group members, I anticipated that high tenure diversity (i.e., heterogeneity) would increase the likelihood of knowledge spillover.

Consistent with the preceding logic, I found that partial stores in which the trained group is more diverse in tenure are more likely to benefit from knowledge spillover. Because stores with low performance diversity are more competitive and such environments are more suitable for information dissemination, I see the highest change in store sales in partial stores with low performance diversity and high tenure diversity of the trained group. In keeping with my theorizing, groups of trained salespeople with similar levels of organizational tenure tend to form strong group identities and are also more likely to benefit from the training as they may practice new tactics together or help each other in implementing taught behaviors. Thus, the reasonable increase in unit-level sales I found among stores with low tenure diversity (i.e., homogeneity) of the trained group is due, in large part, to the enhanced performance of the trained salespeople. However, because such cohesive groups of trained salespeople tend to be less open to teach, share, or practice their knowledge with outsiders, the increase in sales is greatly enhanced when tenure-diversity of the trained groups is high, as in-group and out-group distinctions are less likely to exist. Finally, although trained groups with high tenure diversity are more open to share their knowledge, untrained salespeople lack the motivation to learn in less competitive settings and hence the high tenure diversity, high performance diversity has the lowest change in store sales.

As shown in Table 6, the coefficient of PARTIAL is significant, meaning that working in a partial-training store has a positive effect on the untrained salespeople's performance change even after store differences are accounted for via MMW and prior performance is controlled. Hence, the effect of training spillover is significant. Even more interesting is the interaction between PARTIAL and performance diversity, indicating that the spillover effect is amplified when performance diversity is low. This supports the contention that competition fosters knowledge dissemination from the trained to the untrained salespeople as shown in Figure 2. Budescu and Maciejovsky found similar results in a series of lab experiments that examined information spillover in a decision-making context (e.g., Budescu and Maciejovsky 2005; Maciejovsky and Budescu 2007; Maciejovsky and Budescu 2013). Thus, my findings further corroborate the notion that although tension between cooperative objectives – sharing of information – and competitive incentives – increasing one's outcome and improving one's position and status – may exist, the social interaction process necessitates the sharing of knowledge even when acting in one's private interest. Notably, in high performance diversity stores where competition is low, the spillover effect ceases to exist and the difference between working in a partial store versus a control store becomes non-significant.

Figure 1.3 panel 3a demonstrates that in low performance diversity, and hence more competitive, stores the untrained salespeople are more likely to adopt the type of behavior learned during the training event, providing additional evidence that performance diversity moderates the effects of knowledge spillover on performance. Trained groups that are more diverse in tenure will themselves benefit less from the training, but are more likely to share that knowledge with untrained salespeople (Figure 1.3 panel 3.b). Additionally, the behavior of untrained salespeople is more likely to incorporate new tactics learned by the trained group as a result of knowledge spillover when the trained groups are more diverse. Conversely, those trained groups with strong group cohesion, resulting from low tenure diversity, use the trained skills more frequently. However, the divide between the performance of the untrained and trained groups escalates because the trained group are more likely to withhold their training from untrained salespeople.

Managerial Implications

Our study has several important implications for managers. First, my study demonstrates that training a subset of the sales force can be as effective as training the entire group. Although unit level sales increase as the number of salespeople who receive training increases, for many reasons it may not be feasible or desirable to train all salespeople within a retail unit. Cron and colleagues (2005) identify several factors that have led to increased skepticism among managers as to the value of expensive training efforts. For instance, managers are increasingly faced with pressures to reduce costs and downsize. Most salespeople work for several companies during their career rather than building a lasting career selling for one company, which results in high turnover rates. Additionally, many salespeople question the value of such training programs as they are often pressed for time, and time spent in training reduces their availability in territory. Therefore, it is important for managers to have some assurance that similar performance outcomes could be expected in stores adopting a partial-training approach, in comparison to stores adopting a full-training approach. The findings from the present study provide evidence of such outcomes.

Second, the fact that performance diversity was found to moderate the effects of training on performance (Figure 1a) suggests that managers can use objective store performance measures to distinguish between those retail units that should train the entire sales force and those that can achieve similar outcomes through partial-training. Partial training can save significant time and money for managers when the performance levels of salespeople are close to each other. Such stores provide a competitive setting in which training is more likely to spillover to the rest of the store. This suggests that managers in stores with high performance diversity should attempt to train the entire sales team rather than a subset of the sales team.

Finally, the tenure diversity and performance diversity interaction effect (Figure 1b) has important implications for managers. my study reveals that managers in stores with high performance diversity should train the entire sales force rather than a subset of salespeople.

However, when it is not possible to train the entire sales team, my findings suggest that managers can systematically identify which group of salespeople should be trained so that the entire store benefits from their training. Specifically, managers should choose a group of salespeople who are diverse in tenure for training to enhance the spillover. This is due to my findings that the cohesion of the trained group is beneficial for their individual performance, yet inhibitive for knowledge spillover. Because stores with high performance diversity are less likely to experience spillover due to lower levels of competitiveness, using a tenure-homogenous group of trained salespeople at least retains their enhanced individual performance.

Implications for Future Research

I limited my demographic diversity variable to tenure not only because of its established importance and superiority over other measures, but also due to a lack of variation in other variables such as sex, age, and ethnicity. Future research can expand my work to include these other variables. Also, since companies use a variety of different criteria to choose individuals for training programs, another interesting future direction is contrasting these criteria (e.g. training low-performers vs. top-performers; training rookies vs. veterans). Finally, despite the overwhelming evidence I gather regarding the driving force of competition in spillover, future research can study the moderating role of social networks between salespeople in attenuating the route through observing rivals and strengthening the route through sharing.

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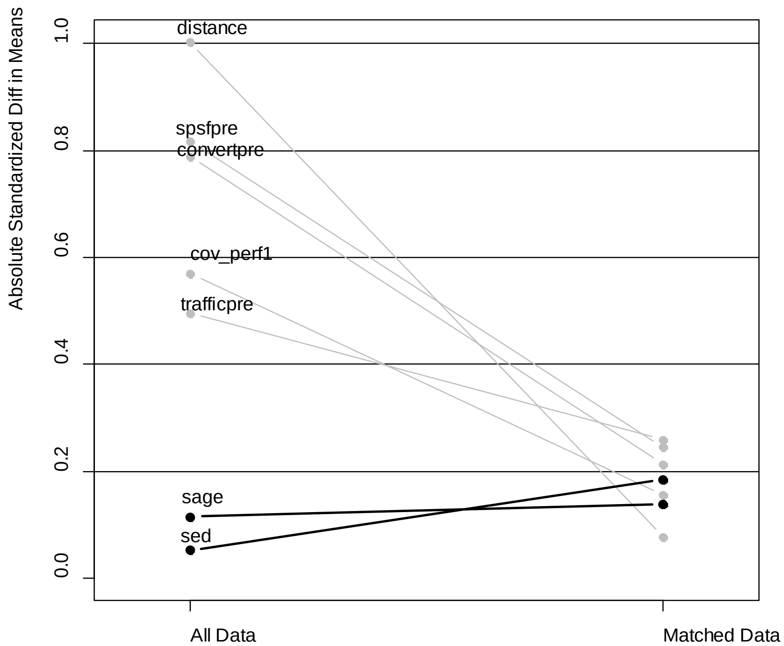
APPENDIX

TABLE A.1
Detailed Balance of Covariats for Trained and Untrained Salespeople before and after Matching in Partial Stores

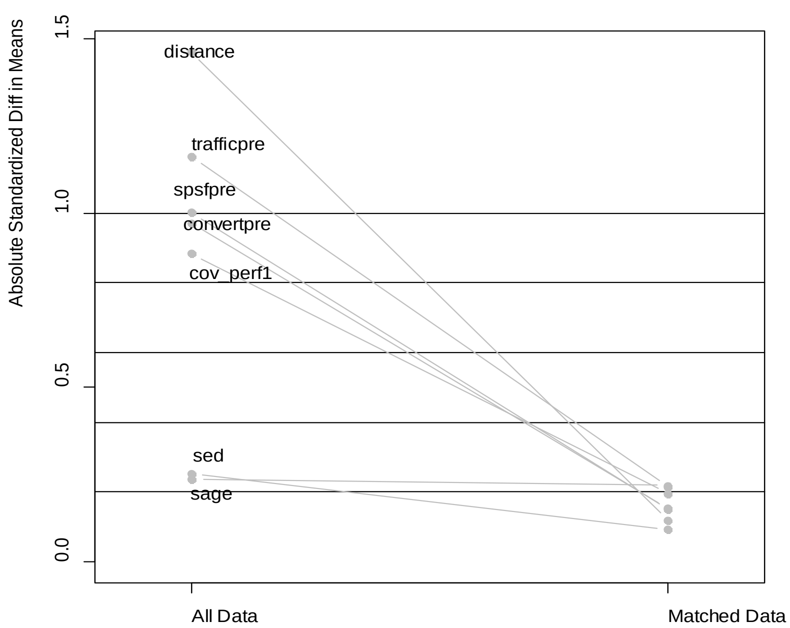
	Detailed Balance Before Matching				**Detailed Balance After Matching**			
Covariates	Means Trained	Means Untrained	SD Untrained	**Std. Mean Difference**	Means Trained	Means Untrained	SD Untrained	**Std. Mean Difference**
PS	.726	.284	.265	**1.883**	.670	.670	.245	**.0001**
Performance	.937	.668	.185	**1.614**	.895	.890	.151	**.034**
PERF_SQR	.045	.053	.055	**-.127**	.032	.030	.031	**.029**
Age	37.710	37.804	7.443	**-.013**	37.698	38.370	7.540	**-.092**
Tenure	38.118	39.273	15.337	**-.077**	38.701	37.404	16.456	**.086**
Income	33445.3	34047.3	7052.3	**-.081**	33707.2	33891.8	6850.6	**-.025**
FULL	.516	.533	.499	**-.033**	.513	.546	.499	**-.066**
Identification	4.290	3.441	2.114	**.446**	4.136	4.027	1.996	**.057**
Benefit level	1.983	2.017	.703	**-.048**	1.997	2.000	.679	**-.004**
Referrals	3.222	2.239	1.932	**.566**	3.006	3.078	1.817	**-.042**
SPEND	535.010	451.480	333.163	**.225**	525.113	518.599	276.725	**.018**
GIFT_SPEND	264.365	211.365	130.514	**.417**	252.588	274.250	131.926	**-.170**
NORM	4.609	3.908	1.774	**.409**	4.430	4.477	1.698	**-.027**
AFFECT	4.387	3.386	1.950	**.545**	4.264	4.125	1.848	**.076**
CONTIN	4.161	3.581	1.971	**.297**	4.109	3.838	2.042	**.139**
Brand value	4.259	3.517	1.909	**.381**	4.127	4.064	1.960	**.033**
Prestige	4.447	3.409	2.037	**.552**	4.229	4.270	2.032	**-.022**
Mystique	4.310	3.448	2.008	**.450**	4.186	4.121	1.885	**.034**
Distinctiveness	4.490	3.497	1.982	**.515**	4.288	4.439	2.088	**-.078**
Store traffic	101.777	97.619	14.607	**.318**	100.713	100.718	13.514	**.0001**
Sales per sq. ft.	1178.726	1139.788	136.688	**.270**	1167.744	1180.347	148.920	**-.087**
ATV	126.864	121.867	15.035	**.323**	125.043	126.384	15.455	**-.087**
Conversion rate	54.709	53.149	5.726	**.244**	54.030	54.247	5.976	**-.034**
Manager's age	49.967	48.080	12.320	**.158**	49.572	48.030	12.836	**.129**
SED	3.033	3.080	.663	**-.070**	3.070	3.100	.608	**-.046**
STENURE	73.519	66.243	46.141	**.159**	71.633	73.551	47.301	**-.042**

Notes: All means represent pre-training means.
Std. Mean Difference = Standardized mean difference, PS=propensity score, PERF_SQR=pre-training performance squared, FULL=binary variable with full-time as 1 and part-time as 0, SPEND=salesperson spending on branded merchandise, GIFT_SPEND=salesperson spending on branded merchandise for gifts, NORM=normative commitment, AFFECT=affective commitment, CONTIN=continuance commitment, ATV=average transaction value, SED=store manager's education, STENURE=store manager's tenure.

FIGURE A.1 – Graphic Summary of Covariate Balance across All Strata for Z_1=Partial Training and Z_2=Full Training



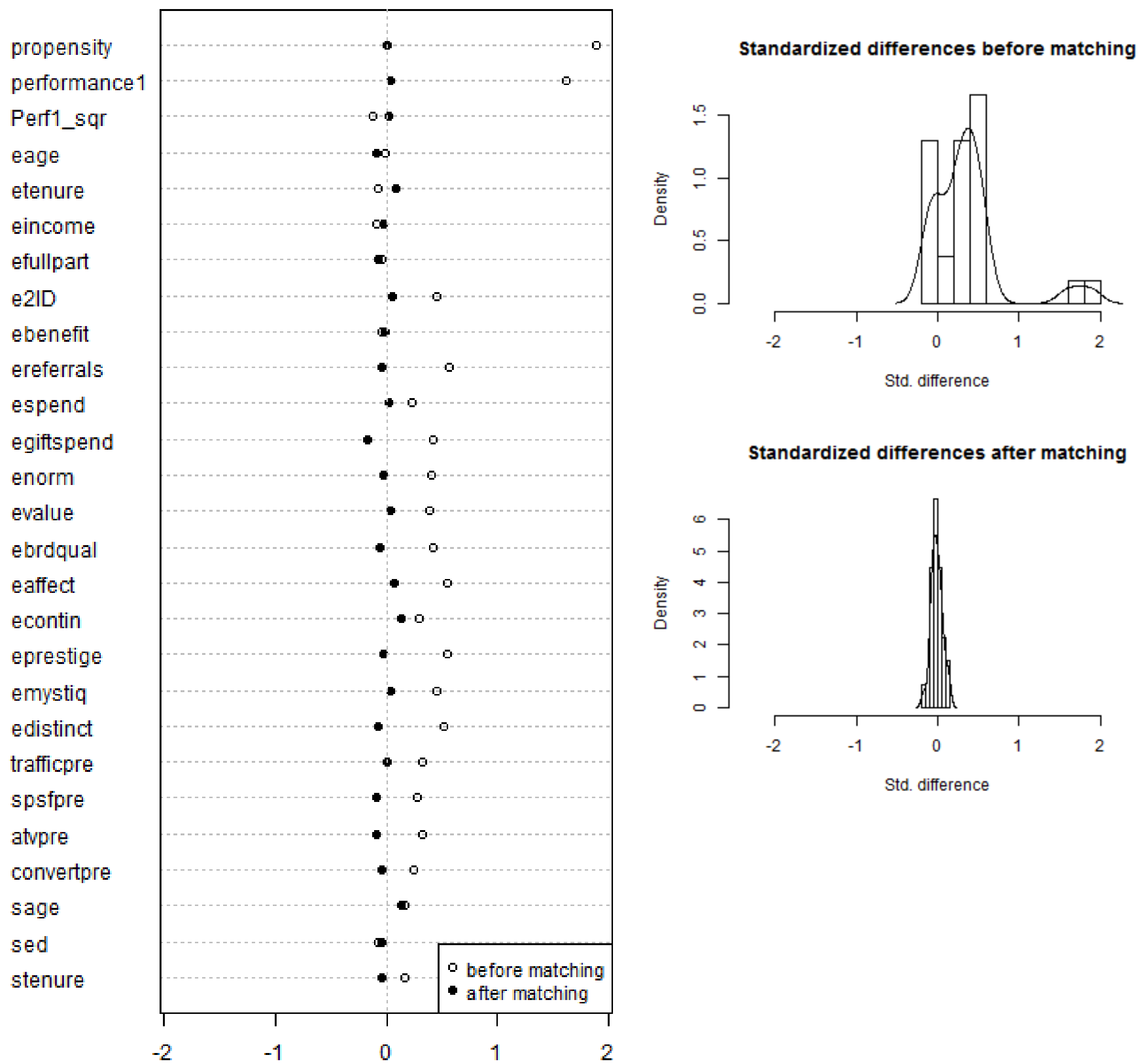
1a - Z_1= Partial Training



1b - Z_2= Full Training

Note: distance = propensity score, trafficpre=pre-training store traffic, spsfpre=pre-training sales per sq. ft., convertpre = pre-training conversion rate, cov_perf1= performance diversity, sed= store manager's education, sage= store manager's age

FIGURE A.2 – Graphic Summary of Covariate Balance for Trained and Untrained Salespeople in Partial Stores



ESSAY 2
THE IMPACT OF OPEN NEGOTIATION ON CUSTOMER FUTURE VALUE

INTRODUCTION

Most “high-involvement” purchases entail extensive negotiations and bargaining. While marketers train their frontline employees to systematically negotiate for better deals, ample evidence suggest that firms are losing their edge to customers who are becoming increasingly well-educated about their options, thanks to the prevalence of information that has tipped the power balance in favor of customers. Today’s empowered customers enter negotiations armed with a clear idea of what they need and the price vicinity that they should be paying for a given product, which helps them squeeze the seller’s margins (Adamson, Dixon, and Toman 2013).

Despite the availability of such information that brings the buyer’s knowledge on par with the seller’s, the distribution of information still remains largely skewed towards the seller when it comes to the “aftermarket” or the “backend” of the deals – i.e. firm’s offerings for financing, insurance, service, maintenance, etc. For instance, although an automobile buyer can collect a plethora of useful information regarding the actual prices paid and the factory invoice price of a desired model as well as its features from websites that provide such information (e.g. truecar.com, Edmunds.com, kbb.com), the information on the most affordable loan for which the customer is eligible is only exposed to the finance manager, who would more likely present another financing option which might be less optimal for the customer but more profitable for the firm (Guillot 2016). Likewise, most B2B software vendors benefit from the fact that their customers are mainly focused on the upfront license prices, due to the availability of such data, rather than on how much they pay on the backend, in software service and maintenance fees, where the bulk of the vendors' profits come from (Scavo 2005).

The information asymmetry on the backend negotiations is a crucial factor in the profitability of firms as American businesses and consumers spend trillions of dollars a year on insuring, financing and servicing products they own (Cohen, Agrawal, and Agrawal 2006). Aftermarket profits have become an integral part of the overall margins of many industries such as industrial machinery, original equipment, computer hardware, prepackaged software, and automotive industry, and in many cases even outstrip profits from selling the product itself (Cusumano 2008; Quinn 1992; Reinartz and Ulaga 2008a). IBM for instance, gains more than 60% of its total revenues from its aftermarket, up from about 35% in 1996. According to National Automobile Dealers Association, more than half of an average automobile dealer's gross profits come from its service department as well as the finance and insurance (F&I) department , surpassing margins from selling new cars and used cars (Reed 2013). Not only aftermarkets can fetch handsome profits for product firms, but their margins can also boost profitability in firms' product markets and drive the overall margins up (Suarez, Cusumano, and Kahl 2013). Boston Consulting Group reports that product companies with a larger aftermarket share of overall revenues deliver higher total shareholder returns (BCG 2012).

Despite such importance, aftermarkets suffer from a dearth of relevant academic research. Focusing on the 'frontend' of the deal, researchers have mainly looked at the impact of negotiation styles at different stages of the negotiation (Adair and Brett 2005), customer characteristics (Morton, Silva-Risso, and Zettelmeyer 2011; Patton and Balakrishnan 2010; Wieseke, Alavi, and Habel 2014; Zettelmeyer, Morton, and Silva-

Risso 2006), and specific negotiation strategies (Bennett 2013; Tadelis and Zettelmeyer 2015) on the outcome of the negotiation.

This essay adds a different shade to the third group of studies by examining the effect of open negotiation in the frontend of the deal, indicated by disclosing the invoice price of a product, on customer profitability in the backend of the deal. In particular I investigate whether information disclosure and its timing can affect customer's immediate future (e.g. finance, insurance or other cross-sold products or services etc.) and distant future (e.g. service) value.

Prior research has demonstrated that a cooperative style in the early stages of a negotiation can build trust and significantly enhance the chances of reaching a deal (Adair and Brett 2005). I theorize that disclosing sensitive information at the early stages of a negotiation can particularly build trust because the well-prepared customer can verify that the disclosed information are in fact, accurate. As a consequence, the trustful customer is more susceptible to trusting the entire process including the backend of the deal, where unlike the frontend of the deal, the customer would not be able to fact-check the frontline employee's claims due to the lack of sufficient relevant information surrounding the backend. Therefore, I hypothesize that the customers to whom sensitive information is disclosed at the early stages of a negotiation would significantly generate more profits in the backend of the deal and more likely to come back for service than others.

Furthermore, I hypothesize that the magnitude of this effect is contingent on the channel through which the customer purchases the product. Unlike walk-in customers, internet customers are generally price-shoppers who expect to receive lower deals (Scott

Morton, Zettelmeyer, and Silva-Risso 2001; Zettelmeyer et al. 2006) and hence are less likely to be affected by information disclosure than walk-in customers.

To test these hypotheses, I report a field experiment carried out at a U.S.-based automotive dealership. 429 real salesperson-customer negotiations were observed and recorded to study the effect of information disclosure on customer future value. The observed transactions fell into three groups depending on whether the invoice price of the car was disclosed at the beginning of the negotiation, disclosed in the middle or at the end of the negotiation, or not disclosed. To ensure that the observations in each condition only randomly differed prior to the negotiation, I used a newly developed matching method called marginal mean weighting with propensity score stratification (MMW-S) which is suitable for multivalued treatment effects. I also drew on two sources of secondary data from the dealership's CRM system, including detailed information on every transaction during a four-year period as well as data collected from the service department indicating whether the customer returned for service. This study makes the following theoretical and managerial contributions.

First, my findings suggest that strategically revealing the invoice price of a product early on in the negotiation can increase customers' profitability in the aftermarket. This finding offers clear and actionable managerial implications since most firms have realized that succeeding in the market does not guarantee success in the aftermarket. A recent study by Bain & Company reveals that many firms utilize only 10% to 25% of their full aftermarket potential for their installed base (Strähle, Füllemann, and Bendig 2012). My results suggest that by applying a simple open strategy in the negotiation, firms can significantly improve their backend margins. Moreover, while salespeople are often incentivized on their immediate sales rather than aftersales, the results imply that a more holistic look at the entire value chain should be used in designing salesforce compensation plans.

Second, the study examines three specific open negotiation behaviors that differ with regard to the timing of information disclosure (i.e., early, late or not disclosed). Prior research has mainly focused on analyzing customer-related negotiation characteristics (Patton and Balakrishnan 2010; Wieseke, Alavi, and Habel 2014), company-related negotiation characteristics (Bennet 2013; Wilken et al. 2010) or sales reps' general willingness to compromise in negotiations (Patton and Balakrishnan 2010). This essay extends prior work by providing a more nuanced analysis of information disclosure, representing an important and specific negotiation approach (Milgrom and Weber 1982; Tadelis and Zettelmeyer 2015).

Third, this paper contributes to prior work on price negotiations that has mainly focused on negotiation outcomes that directly relate to the focal deal, such as buyers' or sellers' profits or the satisfaction with a focal deal (Patton and Balakrishnan 2010; Wilken et al. 2010). Thus, this study extends prior work by providing a more comprehensive analysis of the effects of open negotiation on immediate firm profits as well as various future profit components. This approach therefore is more in line with recent ideas in relationship management, encouraging firms to consider future customer potentials when choosing current sales approaches (Palmatier et al. 2006; Reinartz, Krafft, and Hoyer 2004).

This essay continues as follows. In the next section I will proceed by a brief literature review. Then the conceptual framework and predictions are explained. Then the data collection and the empirical strategy are explained in the method part. Next the results are discussed. Finally general discussion will summarize the findings and conclude the paper by discussing theoretical and managerial implications as well as future directions.

LITERATURE REVIEW

The extant literature falls into two main categories. The first group of studies has looked at price negotiations (Patton and Balakrishnan 2010; Wieseke, Alavi, and Habel 2014; Wilken et al. 2010). This line of research demonstrates that pre-negotiation customer loyalty drives the company's discount giving behavior, which in turn positively affects customers' post-negotiation loyalty intentions (Wieseke, Alavi, and Habel 2014). In addition, this line of research shows that the expectation of a future bargaining interaction affects the negotiated solution (Patton and Balakrishnan 2010).

The second line of research focuses on the impact of information disclosure in an auction setting (Milgrom and Weber 1982; Tadelis and Zettelmeyer 2015). These papers study information disclosure as a matching mechanism between buyers and sellers which increases the competition among buyers and hence benefits the seller through increased prices because of this competition.

However, prior research is subject to at least three major limitations. First, these studies have focused on analyzing customer-related negotiation characteristics (Patton and Balakrishnan 2010; Wieseke, Alavi, and Habel 2014), company-related negotiation characteristics (Bennet 2013; Wilken et al. 2010) or sales reps' general willingness to compromise in negotiations (Patton and Balakrishnan 2010). Thus, important more specific aspects of sales reps' actual negotiation behavior, such as information disclosure and its timing have not been studied.

Second, prior work in this area has focused on various negotiation outcomes that directly relate to the focal deal, such as buyers' or sellers' profits or the satisfaction with a focal deal (Patton and Balakrishnan 2010; Wilken et al. 2010) or customer loyalty intentions (Wieseke, Alavi, and Habel 2014). Thus, important future-oriented quantitative consequences of negotiations, such as cross- and up-selling performance (Schmitz, Lee, and Lilien 2014) or service sales (Ulaga and Reinartz 2011), have been neglected.

Third, previous research has focused on examining various drivers of negotiation outcomes at several detached levels. For instance, prior work examines the separate effects of seller-related variables (Bennet 2013) and deal variables (Zhu et al. 2008). Thus, important other variables, such as channel aspects and their interplay with sales rep variables have not been studied. As displayed in Table 2.1, this study overcomes these gaps and makes three important contributions above and beyond the exiting literature.

TABLE 2.1

Literature Gaps

	Previous Research Relevant to This Study		This Study
	Research on Retail Price Negotiation in General	**Research on Retail Price Negotiation in Dealerships in Particular**	**Research Gaps and Contributions of this Study**
Key studies	Patton and Balakrishnan (2010); Wieseke et al. (2014); Wilken et al. (2010)	Bennet (2013); Busse et al. 2006; Busse et al. (2010); Busse et al. (2013); Morton et al. (2011); Zhu et al. (2008)	
Investigated negotiation outcomes	Investigation of the effects of various negotiation related factors on… …buyers' (Patton and Balakrishnan 2010; Wilken et al. 2010) and sellers' direct deal outcomes (Patton and Balakrishnan 2010), such as profits or satisfaction with the deal. …customer loyalty intentions in the future (Wieseke et al. 2014).	Investigation of the effects of various negotiation related factors on… …price concessions (Busse et al. 2013) …purchase price (Bennet 2013; Busse et al. 2006; Busse et al. 2010; Morton et al. 2011; Zhu et al. 2008) …inspections (Bennet 2013) …trade-in and finance margin (Busse and Silva-Risso 2010)	**Research gap:** Prior research has not looked at open (information disclosure) negotiation and its effect on customer's future value. **Contribution 1: The effect of open negotiation on future value.**
Selective insights regarding negotiation characteristics	• Pre-negotiation customer loyalty drives the company's discount giving behavior, which in turn positively affects customers' post-negotiation loyalty intentions (Wieseke et al. 2014). • The disclosure of cost information affects consumers' reference price (Wilken et al. 2010). • The expectation of a future bargaining interaction influences the bargainers' negotiation style and the negotiated solution (Patton and Balakrishnan 2010).	• Customers engaging in transactions involving a trade-in, focus more on getting good value for the trade-in than for the new product (Zhu et al. 2008). • A serial sales process improves companies' bargaining power and the achieved purchase price as compared to a sequential sales process (Bennet 2013).	**Research gap:** Information disclosure has mostly been viewed as a matching mechanism in auctions rather than a trust-building phenomenon and its effect on future value. **Contribution 2: Open negotiation as a trust-building mechanism reflected in the differential effects of disclosure timing on future value.**
Scope of considered negotiation characteristics	• Detached negotiation characteristics are investigated separately with regard to customer variables (Wieseke et al. 2014; Wilken et al. 2010) or seller variables (Patton and Balakrishnan 2010; Wilken et al. 2010)	• Detached negotiation characteristics are investigated separately with regard to deal variables (Zhu et al. 2008), customer variables (Busse et al. 2010), and seller variables (Bennet 2013)	**Research gap:** The moderating role of channels and product types on the impact of negotiation strategies on outcomes has not been studied. **Contribution 3: The moderating role of channel and product type on the effectiveness of open negotiation.**

CONCEPTUAL FRAMEWORK AND PREDICTIONS

Drawing from studies on information disclosure and trust (Adair and Brett 2005), trust and customer value (Fang et al. 2008) and information asymmetry (Balakrishnan and Koza 1993) I propose that open negotiation at the beginning of the bargaining process positively impacts customer immediate future and distant future value. Moreover, I hypothesize that this effect is moderated by channel of purchase (internet vs. walk-in customers). The conceptual framework is depicted in Figure 2.1.

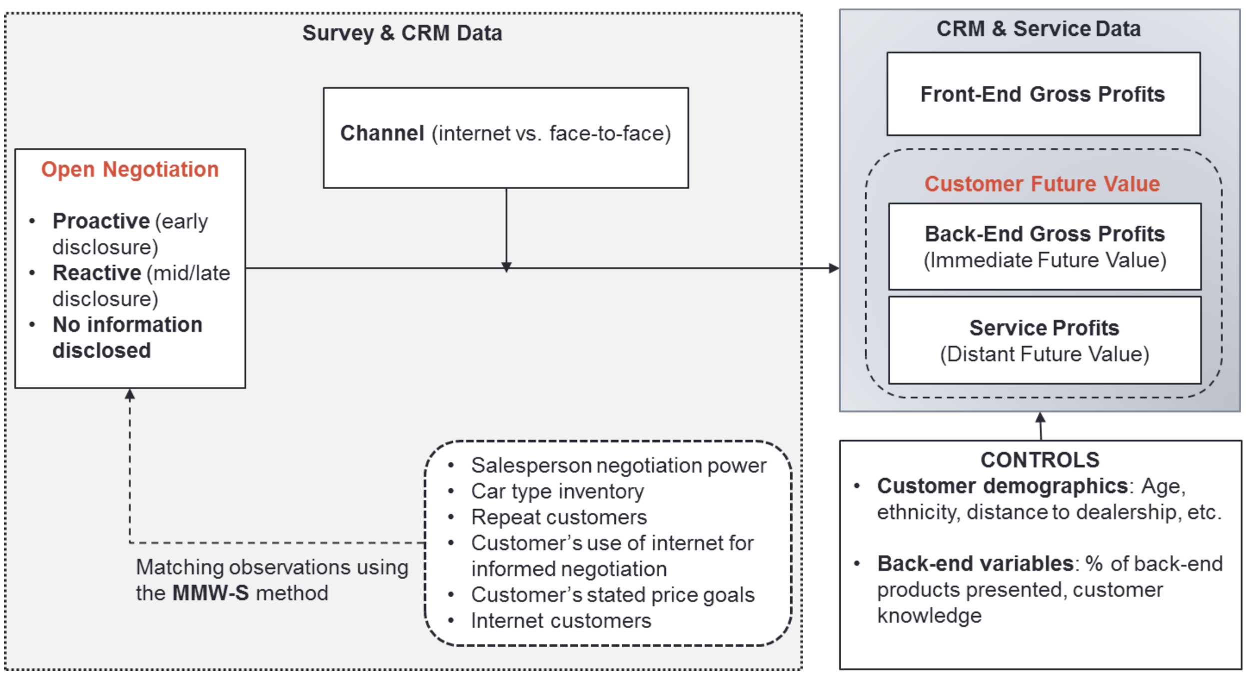


FIGURE 2.1 – The Effect of Open Negotiation on Customer Future Value

The invoice price represents the cost of the car to the dealership and signals the maximum point to which a customer can press for a price concession. Hence the invoice price is considered sensitive information and revealing it would be tantamount to instant loss of money as customers would have a valid reference point to haggle for. Therefore, upon revealing the invoice price, the 'frontend' gross profits, or profits from selling the car at a good price is likely to diminish.

H_1: Revealing the invoice will lower the frontend profits.

On the other hand, information disclosure has shown to increase trust in negotiations (Lunawat 2013; Such et al. 2012). This trust-building can particularly be effective when the customer can verify the accuracy of the disclosed information. In the absence of such verification, the revelation might not particularly build trust, since it would be possible for the seller to communicate false information in order to cheat or manipulate buyer's trust. I argue that such manipulation is less likely to happen on the frontend of the deal, since the information regarding the frontend of many transactions is widely accessible through the internet. In the case of an auto purchase, many websites give the customer a good idea of the invoice price of the desired car with some of them claiming to reveal the correct invoice of the car. In many other purchase decisions, customers have collected ample information about the frontend of the deal that leaves little room for inaccurate information communication. Therefore, on the frontend of most deals, the information asymmetry is low and information revelation is more likely to build trust. Having done their own research before stepping into the negotiation, customers can verify the accuracy of the revealed information and trust the seller for disclosing sensitive information to them.

Moreover, the timing of the disclosure also matters. Researchers have found that at the early stages of the negotiations, most negotiators assume that the other party wants the opposite of what they want (Lytle, Brett, and Shapiro 1999; Thompson 1990; Thompson and Hastie 1990). This assumption makes most buyers start from a competitive position at the outset of the negotiation (Lytle et al. 1999; Simons 1993). Revealing sensitive information at this stage attenuates these competitive presumptions and signals cooperation and willingness to reach a deal (Adair and Brett 2005). However, I argue that information disclosure might not be as effective in the later stages of the negotiation since the parties have already reached a good understanding of each other's wants and the information revelation is more likely to be viewed as a reactive strategy and a late attempt to reach an agreement. Therefore, information disclosure at the beginning of the negotiation is more likely to build trust than in the later stages.

On the other hand, the backend and the aftermarket of the deal are fraught with asymmetric information. Information on interest rates, financing options, APR's , insurance plans, invoice price of add-on products, service and maintenance plans, etc. are often not as accessible as the information on the frontend of the deals. Firms enjoy extensive information rents on the backend and the aftermarket of the deals that allows them to manipulate trustful customers and extract extra profits from them. Moreover, trust is the cornerstone of the future value of customers (Fang et al. 2008). Customers who have trusted the firm are also more likely to come back for service. Therefore, I argue that invoice disclosure at the beginning of the negotiation can gain customer's trust, which can be used by the firm to extract extra profits in the backend and the aftermarket of the deal.

H_2: Invoice disclosure in the beginning of the negotiation is more likely to increase backend profits, and the likelihood of customer's return for service.

I also hypothesize that the purchase channel moderates the salutary effects of early information disclosure on the backend of the deal. In particular, invoice disclosure is more likely to matter for face-to-face negotiations than for online negotiations. Current research suggests that the internet helps customers who have higher disutility to bargain find better deals (Zettelmeyer et al. 2006). Internet customers are generally price-shoppers, with lower search and negotiation costs (Morton, Zettelmeyer, and Silva-Risso 2001; Zettelmeyer 2000). Therefore, internet shoppers are more likely to find a good deal anyways, and the invoice disclosure will not particularly affect their backend or aftermarket profits. Since they are price shoppers, they are more likely to look for a good deal on the backend as well.

H_3: Purchase channel moderates the relationship between invoice disclosure and the backend profits such that the effect of early disclosure is decreased for internet buyers.

METHOD

Research Context

Data was provided by a large national auto dealership chain. The automotive industry provides a suitable context for testing my hypotheses for the following three reasons. First, bargaining is an indispensable part of every auto purchase process. Automobile prices are negotiable and dealerships are notorious for having salespeople who make the negotiation difficult for customers. Second, automobiles have a sizable aftermarket: immediate aftermarket includes financing profits and revenues from cross-selling a variety of different insurance plans and add-on products (e.g. GAP insurance, credit life/disability insurance, anti-theft plan, dent protection, etc.). These immediate future profits are often called ‘backend’ gross profits, as opposed to ‘frontend’ gross profits that come from selling a car at a given price. A more distant aftermarket comes from auto service and maintenance, which according to the National Automobile Dealers Association, make up about 44% of an average automobile dealer’s gross profits, surpassing profits from selling new cars (30%) and used cars (26%; Reed 2013).

Third, internet plays a crucial role in the purchase process, both as a channel through which some customers finalize a purchase and as a platform that spreads detailed price information about each car model. The channel role of the internet has been quickly adopted by dealerships in the past few years such that many auto dealerships today have a dedicated ‘internet department’ (Banks 2002; Reed 2011). The internet departments can often handle the entire sales process online or over the phone. Internet customers use the dealership website to contact the dealer through email or phone. The negotiation starts from there and the internet salespeople finalize the deal through a chain of emails or phone calls.

The internet also disseminates valuable and detailed information regarding the average price paid for a given model in a given time period as well as the invoice price of the car. Websites such as Edmunds.com, truecar.com and kbb.com have become an essential first step in most customers’ auto purchase decision process and sometimes even give an estimated dealer price. Figure 2.2 provides two examples of what a search on these websites can deliver for two different cars.

FIGURE 2.2 – Sample Price Search on Edmunds.com (above) and Truecar.com

Sample and Measures

I used three sources of data to test my hypotheses. First, primary data was collected by using surveys filled out by salespeople as well as research assistants who observed the same auto purchase negotiations. These transactions occurred in 3 different locations of the dealership chain. 429 usable surveys were selected for the analysis. Of these transactions, 64 were lease, 179 were new, and 186 were used car sales. 261 customers were walk-in customers and 168 transactions came through the internet department.

The invoice price of the car, or the cost of a given car for the dealership, can be used by the customer as a reference point for how far he/she can press for a price concession. Thus, revealing or admitting to an invoice price can easily hurt the frontend profits of the transaction, since it provides the customer with a valid basis to bargain for a better discount. In 320 observed transactions, the salesperson did not disclose the invoice price of the car. However in 52 transactions the salesperson disclosed the invoice in the beginning of the negotiation process. In 57 transactions, the salesperson disclosed the invoice price in the middle or at the end of the negotiation.

Besides the information on invoice disclosure, a number of other measures were collected including whether the customer mentioned a specific price goal in the negotiation, whether the customer was a repeat customer, and whether the salesperson thought that the customer had used information on websites such as Edmunds or KBB prior to the negotiation. 22.4% of customers had purchased before, 66.7% were White/Caucasian, and 69.7% stated a specific price goal. The average customer was about 44 years old (M = 44.38, SD = 13.4).

Once a price agreement was reached, the customers did the remainder of the deal in the finance and insurance (F&I) department were the F&I manager proposed financing options (e.g. a proposed APR or finance/lease term), and presented a number of other products and services including GAP insurance, credit disability and credit life insurance, tire and wheel road hazard protection, paint-less guard protection, maintenance plan, etc. The F&I manager also rated customer’s knowledge of the finance and insurance in general. Moreover, the percentage of F&I products and services that were presented by the F&I manager were recorded.

The second source of data was obtained from the CRM records of the chain dealership and included not only detailed information about the observed transactions, but also the entire sales records of all the branches of the dealership going back to four years before the study, comprising more than 105,000 sales transactions. I used this data for two purposes. First, I used information on the frontend and backend gross profits of the observed transactions. Second, I applied prior transactions in the data to compose two measures for two of the variables that I used for the matching procedure explained later. These two variables were salesperson’s negotiation power and the inventory of the car type. Methods used to compose these two measures are explained later in this section.

The third source of data was obtained from the service department of the dealerships and provided me the information on whether customers who signed the observed 429 transactions ever came back to the same dealership to service their car. Moreover, the distance to the dealership and whether the customer lived less than 15 miles from the dealership were attained from customer zip codes.

I used dealership records and applied the procedure explained by Bennett (2013) to compute the inventory of each car type on the lots of each dealership at the time of each transaction. To compute salesperson’s negotiation power, I used the following three steps. First utilizing the entire CRM data, I ran the following quantile regression model (Davino, Furno, and Vistocco 2014; Hao and Naiman 2007) to compute the median price paid for a given car-type in a given month of a given year.

$$Q\tau(P|x) = \inf\{p : \mathrm{Prob}(P \leq p|x = \tau\}, \tau = .5 \quad (1)$$

$$Q\tau(P|x) = X'\beta(\tau) \quad (2)$$

Where P is the final price paid and X is the vector of car-type covariates, month, year, and the dealer. The fitted values of the above regression (equation 2) give the median price paid for a given car-type in a given dealership in a given time. Similar to Busse, Silva-Risso, and Zettlemeyer (2006), I defined the car-type as cars with the same make, model, year, and trim. For instance the fitted values of equation 2 can give the median price paid for a 2012 Infiniti JX35 84113 sold in August 2012 in dealer X.

Next, for each transaction, I divided the final price paid by the customer by the median price computed as explained above. This ratio reflected the degree to which a particular customer had paid compared to others who bought the same product from the same dealer in the same month of the same year. Finally, I computed salesperson negotiation power by averaging the above ratio for each salesperson across his/her entire sales records in previous years to reflect his/her ability to negotiate higher than average prices.

Table 2.2 illustrates the means, the standard deviations, and the inter-correlations of the variables used for the analysis.

TABLE 2.2
Intercorrelation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1.FGR	1																		
2.BGR	0.01	1																	
3.SERV	-.05	.09	1																
4.PRE	-.05	-.05	.11*	1															
5.BEG	-.10*	.13*	.16*	-.01	1														
6.MEN	-.31*	.00	-.03	.02	-.15*	1													
7.INT	-.04	-.14*	-.09	-.03	-.06	-.05	1												
8.NEW	-.33*	.05	.10*	-.01	.21*	.31*	-.08	1											
9.USE	.30*	-.17*	-.14*	.03	-.20*	-.26*	.18*	-.74*	1										
10.LEA	.03	.14*	.10	.01	-.01	-.09	-.12*	-.33*	-.32*	1									
11.INV	-.24*	.01	.19*	.03	.10*	.17*	-.07	.31*	-.41*	.17*	1								
12.NEG	.19*	-.03	.08	-.07	.09	-.05	-.22*	.06	-.14*	.08	.05	1							
13.GOA	-.11*	-.01*	.02	-.05	-.09	.11*	.01	.00	.18*	-.25*	-.10*	-.02	1						
14.F_K	-.09	.14*	.03	.01*	.01	.02	.03	.03	-.05	.04	.01	-.21*	.01	1					
15.F_P	-.18*	.35*	-02	.03	-.04	.11*	.05	.16*	-.07	-.10*	.04	-.31*	-.00	.26*	1				
16.CINF	-.13*	-.10*	.05	.01	.01	.16*	.00	.13*	-.08	-.04	.10*	-.13*	.10*	.07	.12*	1			
17.CL	-.07	-.04	.15*	.01*	-.03	.01	-.12*	-.02	-.02	.05	.04	.00	-.00	.04	-.02	.04	1		
18.AGE	.07	-.22*	.05	.01	-.05	.05	-.10*	.18*	-.01*	-.10*	.04	.21*	.13*	-.04	-.09	.12*	.05	1	
19.WHI	.03	-.08	.06	.02	.01	.07	.03	.17*	-.13*	-.02	.07	.11*	-.01	.12*	-.00	.09*	.02	.26*	1
M	1311	1186	.34	.22	.12	.13	.39	.42	.43	.17	25.75	.008	.70	4.90	.69	.28	.39	44.36	.67
SD	2506	1178	.47	.42	.32	.34	.49	.49	.50	.38	23.38	.019	.46	1.32	.24	.45	.49	13.41	.47

*$p < .05$.

Notes: FGR = frontend gross profits, BGR=backend gross profits, SERV=binary variable with 1 if the customer came back for service, PRE=previous customer, BEG=invoice disclosure in the beginning, MEN=invoice disclosure in the middle or the end, INT=internet customer, NEW=new car, USE=used car, LEA=lease, INV=inventory of the car-type at the time of the transaction, NEG=salesperson negotiation power, GOA=did the customer state a specific price goal, F_K=F&I manager’s rating of customer knowledge, F_P=what percentage of F&I products and services did the F&I manager present, CINF=salesperson’s evaluation of whehter the customer had searched for price on the internet, CL=whether the dealership was close (less than 15 miles) to the customer, AGE= age, WHI=if the customer was white/caucasian.

Empirical Challenge

To make this field experiment as close to a randomized lab experiment as possible, I had to account for a priori differences that might lead to a selection bias. In other words, I have to account for customer-, salesperson-, and dealer-specific covariates that lead to the selection of one of the three conditions: early disclosure of invoice, mid/late disclosure, and no disclosure. Randomized experiments guarantee that the treated and the control units are only randomly different from one another on all important pre-treatment background covariates. Ignoring a priori dissimilarities leads to selection of a treatment and a control group that are systematically different from the very beginning, which biases any inference based on their post-treatment differences.

As a remedy, matching and weighting methods based on propensity scores (Rosenbaum and Rubin 1983) have increased in popularity and complexity among researchers dealing with observational (non-randomized) data across various disciplines such as political science (Ho et al. 2007), education (Hong and Raudenbush 2006), sociology (Morgan and Harding 2006), economics (Imbens 2004), psychology (Harder, Stuart, and Anthony 2010), and statistics (Rubin 2006). These methods aim to create treatment and control groups that look only randomly different from one another on confounding covariates, and hence are comparable (Stuart 2010).

Regression adjustment and other similar methods do not alleviate selection bias in field experiments and even creates further bias (Ho et al. 2007). Especially when the treated and control groups have different distributions of covariates, controlling for covariates leads to extrapolation to unmatched areas where control units are accompanied by treatment units or vice versa. This makes the direction of causality extremely sensitive to minor modifications in the model (Ho et al. 2007; King and Zeng 2007). By deleting or weighting the unmatched observations, matching methods ensure that treated and control units were similar to each other before the treatment was applied.

Besides the selection bias, my data poses two additional challenges. First, while most matching methods are designed for two-level treatment variables (i.e. treatment vs. control), my treatment variable contains three levels (i.e. information disclosure at the beginning vs. information disclosure in the middle/end vs. nondisclosure). Also the sample size does not allow me to freely delete unmatched observations. To attenuate this problem I utilized a recently developed method called marginal mean weighting through propensity score stratification (MMW; Hong 2012, 2010; Hong and Nomi 2012) that is superior to similar weighting methods (e.g. inverse probability weighting; IPW) and can be applied to multi-valued treatment analyses (Hong 2012; Hong and Hong 2009). In this method, for each treatment level the sample is stratified into various groups where in each group observations receiving that treatment have similar covariate distributions with others. Observations are then weighted based on the stratum they fall in and computed weights are used in subsequent statistical analyses. I explain the procedure in more detail in my results section.

Selection of Covariates for Matching

The covariates selected for matching should either theoretically or empirically affect the treatment assignment or correlate with the dependent variables (Steiner et al. 2010; Stuart 2010). To select the covariates for matching, I ran several diagnostic tests in the form of multinomial logit regressions to see which variables better predict the treatment assignments. Moreover, I used theory to argue for selecting some of the variables.

As explained earlier, salesperson negotiation power indicates the extent to which a given salesperson obtains higher than average margins from customers. Thus I included salesperson's negotiation power as a covariate for the matching procedure because a powerful negotiator is less likely to reveal the invoice price which will significantly hurt the chances of signing a profitable frontend deal and earning a good commission.

I also included the inventory of the car-type at the time of the transaction for the following reasons. First, when the supply of a given model parked on the lots of the dealership increases, the basic economic rules indicate that the dealer should be willing to sell the model at a lower price. Invoice disclosure allows both parties to shorten the negotiation and agree on a price, which would be a lower price than when the salesperson negotiates without revealing the invoice. Second, with more cars of the same model on the dealership lots, the opportunity cost of losing a potential customer in order to wait for a potentially higher-paying future buyer increases due to inventory costs. For instance, if only one car of a given model remained on the lot, the dealership could afford to wait for a higher paying buyer by negotiating harder with customers. Moreover, the diagnostic tests as well as the inter-correlations revealed that the inventory of the car model at the time of purchase significantly predicted invoice disclosure.

I also included a number of other covariates that theoretically or empirically affected invoice disclosure. Whether the customer specifically stated a price goal was included as a binary covariate for the matching procedure. Recent findings suggest that stating a specific price goal by the customer can significantly reduce the agreed price

(Busse, Israeli, and Zettelmeyer 2016). Whether the customer was a repeat buyer could also affect information disclosure since repeat customers are shown to enjoy an easier negotiation process (Wieseke et al. 2014). Whether the customer was an internet buyer and whether the salesperson believed that the customer had searched over the internet prior to purchase were also added to the covariate list.

RESULTS

MMW-S

The recently developed method of MMW-S (Hong 2012) is applied in disciplines such as education and epidemiology (Hong and Hong 2009; Hong and Raudenbush 2006) and is extremely well-suited for multi-treatment analyses involving selection bias (Hong 2012). I used the following three steps to match the stores with MMW-S.

First, for each of the treatment conditions, T_1 = early disclosure, T_2= late disclosure, and T_0= nondisclosure, I ran a binary logistic model to determine the probability that T_i is chosen over the other two conditions, given the covariates. Next, I stratified the whole sample into different strata based on the fitted values of the logistic model (i.e. propensity score) such that in each stratum, the relevant covariates as well as the propensity score had the same distribution for those observations that received that treatment and those which did not. For instance Table 2.3 shows the stratification for T_0= nondisclosure and the means for the propensity score and, as a sample of the covariates, the car-type inventory.

TABLE 2.3
Balance for the Logit of the Propensity Score and Car Type Inventory for Nondisclosure Condition across the 4 Strata

	Invoice Not Disclosed ($T_0 = 1$)			Others ($T_0 = 0$)		
Stratum	n	M_{PS}	M_{INV}	N	M_{PS}	M_{INV}
1	62	.5931	53.13	45	.5952	52.62
2	80	.7271	33.96	27	.7238	31.63
3	80	.8093	11.81	26	.8025	16.58
4	98	.8546	4.04	11	.8524	3.81
Total	320	.7607	22.97	109	.7025	33.89

% of balance improvement in mean difference across Subclasses

Propensity score	95.65%
Car-type inventory	96.22%

Notes: M_{PS} = mean of the logit of the propensity score, M_{INV} = mean of car inventory.

For example Table 2.3 shows that in stratum 2, 80 of the transactions have nondisclosed invoice price and 27 have disclosed the invoice, either in the beginning or disclosed in the middle/late disclosure. The mean of the propensity score and other covariates such as car-type inventory is closely matched. Figure 2.3 gives a graphic summary of the matching for the nondisclosure condition (T_0 = undisclosed invoice price). The first panel (above) demonstrates the distribution of the propensity score for treatment and control units stratified across four subclasses. Panel below summarizes covariate balance measured as standardized mean difference between treatment and control group across all the strata.

It is noteworthy that there is no right number of strata for the matching procedure. For each treatment condition, I stratified the sample into various sets of subclasses and chose the number of subclasses for each condition that delivered the best balance between the covariates.

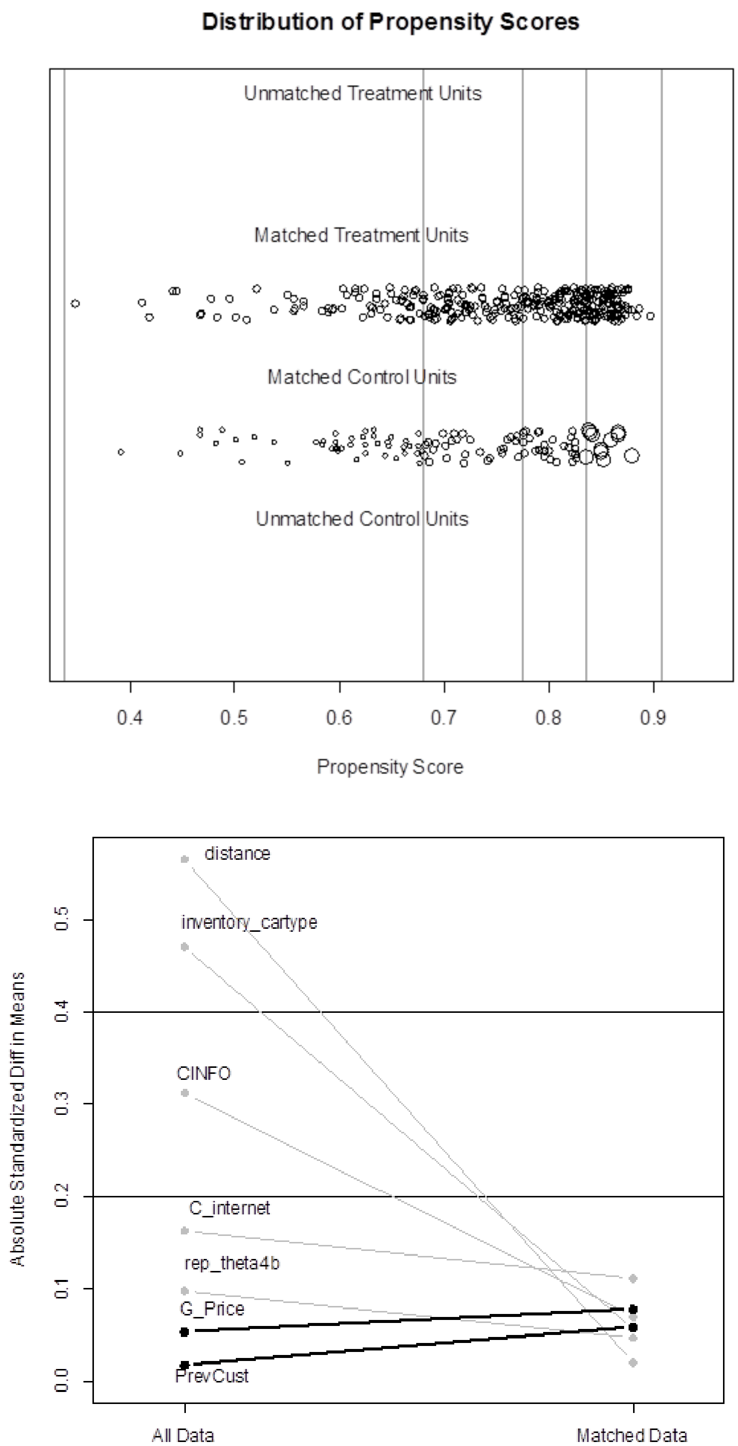


FIGURE 2.3 – Summary of Matching for T_0=Invoice Not Disclosed

As the final step, stores in treatment group T_i and stratum S receive marginal mean weights computed as MMW = $(n_S/n_{Ti,S}) \times prob[(T_i) = 1]$ where n_S is the number of stores in stratum S, $n_{Ti,S}$ is the number of stores in stratum S that are assigned to treatment T_i, and $prob[(T_i) = 1]$ is the overall proportion of the stores in treatment group T_i. Table 2.4 presents the complete stratification information with computed marginal mean weights. As an example, early disclosure observations (T_1=1) in stratum 4 received a weight of (108/21) × (52/429) = .62. I used computed marginal mean weights as regression weights in my subsequent store-level analysis.

TABLE 2.4
Summary of Strata and Computed Marginal Mean Weights

	T_0 = Not Disclosed				**T_1 = Disclosed in the Beginning**				**T_2 = Disclosed Middle/Late**			
Str.	MMW	T_0=1	T_0=0	Total	MMW	T_1=1	T_1=0	Total	MMW	T_2=1	T_2=0	Total
1	1.28	62	45	107	1.85	8	100	108	2.37	8	135	143
2	.99	80	27	107	1.18	11	95	106	1.26	15	128	143
3	.98	80	26	106	1.81	12	95	107	.56	34	109	143
4	.83	98	11	109	.62	21	87	108	-	-	-	-
Total				429				429				429

Note: MMW = Marginal Mean Weights.

Frontend Gross and Backend Gross

The results of weighted least squares regression (WLS) with the MMW’s as regression weights revealed that consistent with my hypotheses, invoice disclosure significantly reduced the frontend gross profits. However, revealing the invoice at the beginning of the negotiation process significantly helped the backend gross profitability of the deal supporting my hypotheses. Figure 2.4 demonstrates these findings. Moreover, Table 2.5 summarizes the results of the WLS with the backend gross profits as the dependent variable.

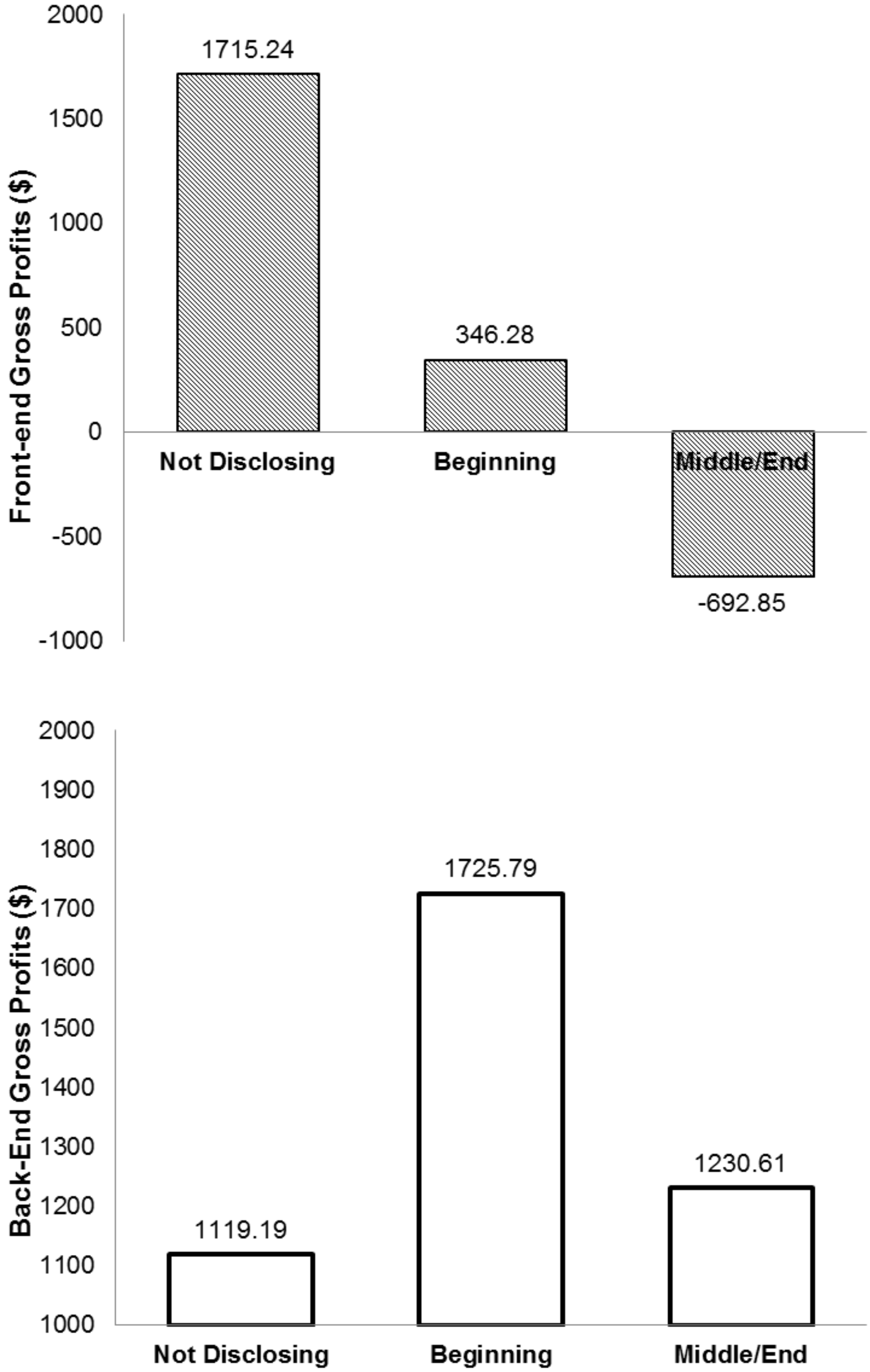


FIGURE 2.4 – The Effect of Invoice Disclosure on Frontend and Backend Gross Profits

TABLE 2.5
WLS Analysis of the Effects of Invoice Disclosure on Backend Gross Profits

Dependent Variable *Backend gross profits*		
	B	S.E.
Intercept	**996.80***	(325.84)
Early disclosure	**845.84***	(200.53)
Late/middle disclosure	-212.19	(196.90)
Internet customer	**-331.84***	(127.96)
Early disclosure × internet customer	**-691.85***	(315.21)
Late/middle disclosure × internet Customer	341.53	(341.52)
New car	**-480.27***	(166.65)
Used car	**-643.87***	(161.94)
Customer knowledge rated by the F&I manager	37.73	(41.36)
% of products presented by the F&I manager	**1943.43***	(240.18)
Age	**-15.56***	(4.22)
White/Caucasian	-122.03	(116.32)
R^2	.290	
Adjusted R^2	.270	

*$p < .05$; *Notes*: weighted least squares regression with MMW as regression weights.

The results also support the moderating role of channel on the impact of information disclosure on the backend gross profits. As hypothesized, invoice disclosure for internet customers does not significantly affect the backend profits of the deal. Figure 2.6 demonstrates the moderating role of internet on the effect of invoice disclosure on the backend profits.

Service

Finally, I ran a weighted binary logistic model with MMW's as regression weights and service as the dependent variable. The results indicate that even after controlling for the distance to dealership, early disclosure of invoice price still significantly predicts whether the customer comes back for service to the dealership. Figure 2.5 and Table 2.6 illustrates the results of this regression.

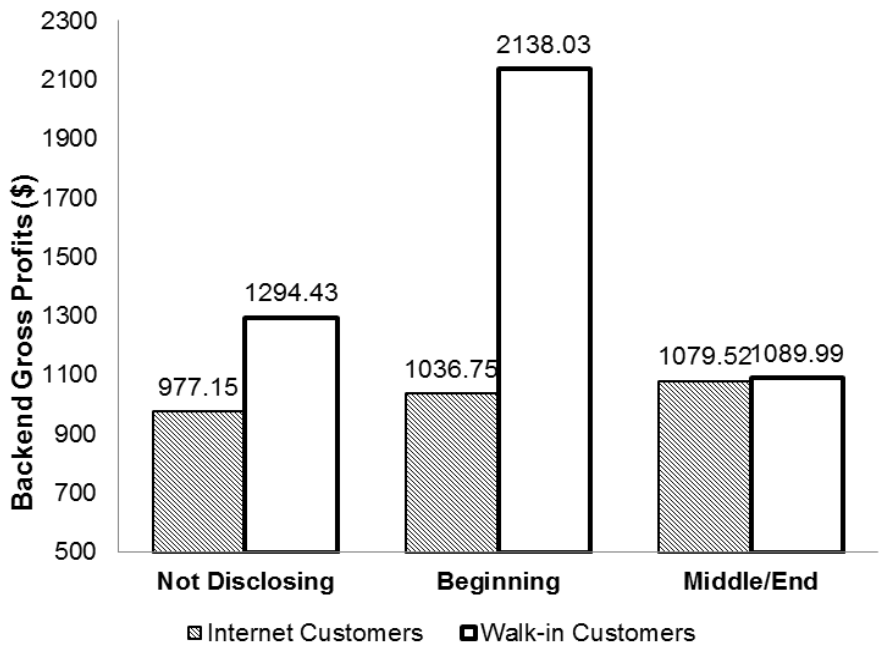


FIGURE 2.5 – The Moderating Role of Channel

TABLE 2.6
Weighted Logistic Analysis of the Effects of Invoice Disclosure on Returning for Service

Dependent Variable *Service*		
	B	S.E.
Intercept	.87	(.86)
Distance within 15 miles?	**.89***	(.21)
Early disclosure	**.93***	(.40)
Late/middle disclosure	-.17	(.38)
Internet customer	-.33	(.25)
Early disclosure × internet customer	.08	(.62)
Late/middle disclosure × internet Customer	.81	(.64)
New car	.10	(.31)
Used car	-.41	(.31)
Age	-.01	(.01)
White/Caucasian	.24	(.23)
AIC	529.66	
BIC	573.70	

*$p < .05$; *Notes*: weighted least squares regression with MMW as regression weights.

GENERAL DISCUSSION

The main profit engine of many product firms is not the sales of the products they offer, but rather, the backend and the aftermarket profits. Moreover, many of the products for which a significant aftermarket exists are considered ‘high-involvement’ purchases, and hence are bought after extensive buyer-seller negotiations. This extensive interaction with the customer provides companies the unique opportunity to leverage the initial price negotiations with customers to enhance their future value (Reinartz and Ulaga 2008b). Since trust is the centerpiece of customer future value (Fang et al. 2008; Sirdeshmukh, Singh, and Sabol 2002), an open negotiation might be able to gain this trust (Adair and Brett 2005) and hence impact customer’s future profitability.

Especially because the internet has helped customers become better-informed about the frontend of deals, it has become increasingly difficult to eke out margins out of negotiations. However, the information is still asymmetric when it comes to the backend or the aftermarket profits since the internet provides little information on these important pieces of a deal. Gaining customer’s trust by disclosing invoice price of a product, which is sensitive information but verifiable by the customer, can particularly help firms on the backend and the aftermarket where customers’ knowledge is not on par with their knowledge about the frontend of the deal.

To address this issue, this essay examines how sales reps’ open negotiation behavior affects customers’ immediate value, their proximal future value, and their distant future value. 3 sources of data were obtained from a major national auto dealership chain to investigate the effect of information disclosure on customer’s future value. Findings suggest that consistent with the hypotheses, disclosing the invoice price of a car at the beginning of the negotiation process significantly enhances the backend gross profits of the car and the likelihood of customer's returning for service, compared to disclosing the invoice in the middle/late or the nondisclosure condition. Moreover, this effect was moderated by the channel through which the customer purchased the car, as invoice disclosure did not affect internet customers.

Theoretical Implications

This essay makes the three major contributions beyond the existing literature. Each of these contributions suggests various opportunities for future research.

First, the study is the first to examine sales reps' open negotiation behavior as well as the timing of the information disclosure (i.e., early or late open negotiation and concealed negotiation). The analysis advances prior work in two ways. On one hand, the study extends prior sales research on price negotiations (e.g. Patton and Balakrishnan 2010; Wieseke et al. 2014) by introducing the concept of open negotiation. In particular, I demonstrate how salespeople can build customer trust by revealing the information that, despite being sensitive, is easily verifiable by the customer due to the variety of different websites that disseminate similar information. However, this trust is eventually manifested in higher customer value in the proximal and distal future, where the information is asymmetric and favors the seller. These findings build on behavioral negotiation strategy (Neale and Northcraft 1991) which emphasizes the value of revealing and concealing information on negotiation outcomes and adds to prior work on information disclosure in auctions (Milgrom and Weber 1982; Tadelis and Zettelmeyer 2015) that has looked at information disclosure as a matching mechanism between buyers and sellers. Moreover, this research advances these studies by investigating the differential effects of the timing of information disclosure. Future research can extend this work by looking at the effect of other aspects of an open negotiation such as the differential effect of disclosing different types of information (e.g., average sales price of product, average margin of product for seller, average price at other outlets) on profitability and customer value.

Second, this study is the first to examine the effects of sales reps' negotiation behavior on customers' proximal and distal future value. We thus extend prior sales research on price negotiations that has either focused on negotiation outcomes that directly relate to the focal deal, such as buyer or seller profits or satisfaction with a focal deal (Patton and Balakrishnan 2010; Wilken et al. 2010), or affect customer loyalty attitudes (Wieseke, Alavi, and Habel 2014).

Third, the results also shed light on the interplay of salespeople's open negotiation behavior and the purchase channel, advancing current research that separately studies customer-level and seller-level factors(Patton and Balakrishnan 2010; Wieseke et al. 2014; Wilken et al. 2010).

Results indicate that the effectiveness of open negotiation behavior strongly depends on the negotiation channel. While early open negotiation behavior is particularly effective in heightening future customer value in face-to-face negotiations, the positive effect disappears for internet customers. Future research can identify other contingency variables such as the context (B2C vs. B2B) or whether the customer has obtained a competitor's quote prior to the negotiation.

Managerial Implications

This study has a number of actionable implications for practitioners. First, most firms incentivize their sales reps based on short-term negotiation outcomes, such as sales margin or number of units sold. However, I recommend firms to focus on the entirety of immediate deal and proximal and distal future outcomes, when assessing and rewarding their sales reps' negotiation performance. This is particularly important since many of the backend aftermarket transactions have both, higher margins and more repeating occurrences than the focal deal. Specifically, this study's findings indicate that sales reps' open negotiation behavior has a strong impact on customers' attitudes and behaviors which can carry over to influence even distal future customer value. Therefore, in order to motivate their sales force to maximize overall customer value, firms have to adapt their performance measurement and control systems to account for these long-term effects of salespeople's negotiation behavior. To direct their salespeople towards potentially sacrificing immediate customer value in exchange for superior future customer value, firms could extend the set of key performance indicators for performance evaluations to accommodate for future aftermarket success.

Second, empirical evidence reveals that many firms today conceive their product sales and aftermarket sales as two separate and detached businesses (Jasmand, Blazevic, and de Ruyter 2012). However, this paper calls for a better analysis of the interdependencies between their frontend, backend, and service departments. Findings demonstrate that a trust-building negotiation in the front-end of the deal is a strong driver of various types of future customer value. Thus, firms should institutionalize the cooperation between their various customer touchpoints in order to maximize the overall customer value (Homburg, Jozić, and Kuehnl 2015). For instance, firms could encourage a systematic job rotation for their service, aftersales, and sales personnel to enhance the abilities and the knowledge of their customer-contact employees regarding all potential touchpoints and encourage the teamwork across these touchpoints.

Third, I advise firms to educate and school their sales force on open negotiation behavior. For instance, firms could amend existing sales force steering instruments, such as sales trainings and development centers, with sections on open negotiation. Moreover, I recommend firms to adapt their specific incentives and guidelines based on their priorities. In particular, firms willing to secure the immediate front gross profits might want to motivate their sales reps to conceal the invoice price information. However, for firms focusing on heightening future customer value, the study an early open negotiation behavior. Finally, we recommend firms to vary their guidelines and incentives with respect to the focal negotiation channel. While early open negotiation behavior is particularly effective in heightening future customer value in face-to-face negotiations, salespeople who manage internet leads would not particularly benefit the future profitability of the customer by revealing the invoice.

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