Huanhuan Shi, Shrihari Sridhar, Rajdeep Grewal, & Gary Lilien

Sales Representative Departures and Customer Reassignment Strategies in Business-to-Business Markets

When a sales representative (rep) leaves a business-to-business firm, a crucial link with the rep's customers becomes severed. The firm reassigns those customers to different sales reps (either existing reps or new hires) in a manner that mitigates potential sales losses. What causal effect do sales rep departures have on customer-level revenue, and which sales rep replacement strategies are more effective? Using data from a *Fortune* 500 firm and a difference-in-differences analysis with correction for selection bias, the authors show that sales rep transitions lead to 13.2%–17.6% losses in annual sales. New hires are less effective than existing sales reps in mitigating sales losses. Existing sales reps who are similar (vs. dissimilar) to the departing reps (in terms of past industry experience) are more effective in mitigating sales losses; however, reps with high past performance do not exhibit greater efficacy for mitigating sales losses than reps with average or low past performance. The analysis presents means to quantify the economic consequences of losing a sales rep and to determine how to reassign customers to sales reps according to the resulting economic impact.

Keywords: business-to-business marketing, customer assignment strategies, causal inference, difference-in-differences, sales representative departure

Online Supplement: http://dx.doi.org/10.1509/jm.15.0358

Sales representatives (reps), as the faces of the selling firm to buyers, are crucial links between buyers and sellers in business-to-business (B2B) markets. Their ability to link the needs of potential customers (accounts) with the offerings or solutions provided by their firm is a key determinant of the financial performance of B2B firms (Ahearne et al. 2010; Kumar, Sunder, and Leone 2014). Zoltners, Sinha, and Lorimer (2012, p. 521) estimate that U.S. B2B firms spend approximately \$800 billion annually on sales forces, or roughly 7% of sales, entrusting these salespeople "with a company's most important asset: its relationship with its customers. Often salespeople have considerable control over this relationship; to some customers, the salesperson *is* the company." Thus, when a sales rep leaves voluntarily, the potentially adverse financial consequences for the firm could be significant (Bendapudi and Leone 2002; Palmatier, Scheer, and Steenkamp 2007). Sales rep turnover is not only problematic but also relatively common; according to the U.S. Bureau of Labor Statistics (2013), the annual turnover rate among B2B sales reps is 22%, exposing approximately \$1.6 trillion[1] in customer sales to the risk of sales rep turnover. This risk arises because sales managers must reassign the customers of a departing sales rep to one or multiple replacements in the hopes that these replacement reps can reestablish and grow the customer relationships—a deeply challenging task.

Considering the seriousness and prevalence of the issue of sales rep turnover, we address two key questions in this research: (1) What is the magnitude of the causal effect of sales rep departures on customer-level revenue? And (2) What relative effectiveness do alternative sales rep replacement strategies offer? The answers can assist firms that need effective reactive strategies to find appropriate replacement sales reps. We focus on voluntary turnover, such that the sales rep leaves on his or her own accord, as opposed to reps who are terminated by the firm. Specifically, we establish a causal link between sales rep transition and customer sales by conducting a difference-in-differences analysis of sales changes one year after versus one year before a sales rep's turnover. The transition

Huanhuan Shi is Assistant Professor of Marketing, College of Business Administration, University of Nebraska–Lincoln (e-mail: hshi4@unl.edu). Shrihari Sridhar is Center for Executive Development Professor and Associate Professor of Marketing, Mays Business School, Texas A&M University (e-mail: ssridhar@mays.tamu.edu). Rajdeep Grewal is Townsend Family Distinguished Professor of Marketing, Kenan-Flagler Business School, University of North Carolina at Chapel Hill (e-mail: grewalr@unc.edu). Gary Lilien is Distinguished Research Professor of Management Science in Marking and Research Director of Institute for the Study of Business Markets, Smeal College of Business, Pennsylvania State University, and Distinguished Professor of Marketing, University of Technology Sydney (e-mail: glilien@psu.edu). The article benefited from feedback of Sonny Lam and Stephan Volpers and seminar participants at the Theory + Practice in Marketing conference in Atlanta, June 2015; ISMS Marketing Science conference in Baltimore, June 2015; and AMA Summer Educators' Conference in Chicago, August 2015. Michael Ahearne served as area editor for this article.

[1]This calculation is based on a 22% turnover rate and \$7,399 billion in B2B sales in 2013 (http://www.census.gov/wholesale/index.html).

ISSN: 0022-2429 (print)
1547-7185 (electronic)

refers to the combination of the exit of a previous sales rep and the reassignment of the affected customers to other sales reps. As a benchmark, we consider any change in sales among matched customers that did not experience any sales rep transition. We control for the endogeneity induced by the nonrandom departure and nonrandom reassignment strategy undertaken by the sales manager. In addition, to quantify heterogeneity in sales rep transition effects, we differentiate the causal effects in situations in which managers reassign the customers of departing sales reps to either new hires or existing sales reps. Finally, for reassignment to an existing sales rep, we study how the transition is moderated by the replacement reps' similar customer base (proxy for similar industry experience) and past performance level (proxy for selling ability), given sales managers' likely beliefs about what constitutes a good replacement (e.g., Gardner 2005; Groysberg, Lee, and Abrahams 2010).

We test our proposed model with customer-level data from a leading U.S. distributor of electrical component products. Using information about departing and assigned sales reps for a subset of customers who experienced sales rep transition and comparable data for a large set of customers who experienced no sales rep turnover, we find a 13.2%–17.6% annual decease in customer sales, on average, from sales rep transition in the firm in question. Customers reassigned to new hires exhibited a 21.6% sales loss, and those reassigned to existing sales reps exhibited an 11.0% sales loss. The firm in question thus could expect sales rep transitions to lead to \$10.65 million–\$14.20 million in sales losses. However, over a longer time window (i.e., ten quarters after departure), the sales losses among customers reassigned to both new hires and existing sales reps begin to diminish (e.g., for new hires, 12.5% sales loss over ten quarters vs. 21.6% for one year).

Our detailed analysis also reveals that among customers reassigned to existing sales reps, more similar industry experience between the departing and the replacement sales reps helps mitigate sales losses. If the firm reassigns average-performing reps without common industry experience to customers, the sales loss is 31.4% ($p < .05$). When these average performers instead are similar to the departing reps, the sales loss is not significantly different from zero (1.7%). Yet our results do not support any statistically significant loss mitigation effects of high-performing sales reps. Thus, similarity in the rep's customer base, rather than his or her past performance, is key for mitigating losses. This finding provides new theoretical and managerial perspectives on sales force management strategy.

We also contribute to general sales literature suggesting that a high turnover rate correlates with poor performance (Darmon 1990; Subramony and Holtom 2012; Ton and Huckman 2008), by quantifying the causal effect of sales rep transition on customer-level sales. Our customer-level analysis enables us to correct for the endogeneity from sales rep departure and replacement assignment decisions and thus obtain causal effects. By taking advantage of variations in replacement strategies at the customer level, we also can causally quantify the relative effectiveness of different replacement strategies and inform prior conceptual and qualitative sales research (e.g., Bendapudi and Leone 2002). The sample comes from one typical B2B distributor, so the magnitude of the causal effect of sales rep transition and the effectiveness of replacement strategies might not apply directly to other organizations. Yet our approach can be generalized to other sales organizations with different selling processes (e.g., team selling), and sales managers can use our method to evaluate the impacts of sales rep transitions and thereby design better replacement strategies.

In the next section, we discuss the conceptual background for our work and present our research questions. Then, we describe the institutional setting and data, model setup, and identification strategies. Finally, we present the results and discuss their implications.

Conceptual Background and Research Questions

Our goal is to quantify the effects of sales rep transition on customer-level performance. We define sales rep transition as a combination of two events: the departure of a sales rep from a firm (and customer account), often referred to as turnover, and the reassignment of the customer account to a replacement sales rep. We first summarize the literature on financial cost of sales rep departure and sales rep assignment. Subsequently, we draw from the literature on sales rep capabilities, as well as multilevel trust between buyers and sellers (i.e., interfirm and interpersonal trust), to develop research questions concerning the effects of sales rep transition on customer-level revenues.

Review of Relevant Literature

Financial cost of sales rep departure. The financial cost associated with sales rep turnover consists of both direct (e.g., recruiting and training new or replacement sales reps; Chandrashekaran et al. 2000; Churchill et al. 1985) and indirect (e.g., loss of full realization of future revenues from customers served by departing sales reps; Bendapudi and Leone 2002; Boles et al. 2012) costs. Direct costs are associated with real cash outflows and are easy to quantify; indirect costs are intangible (O'Connell and Kung 2007; Richardson 1999). To quantify these indirect costs, we turn to Darmon (1990), who assesses direct costs at the sales rep level using accounting data but measures indirect costs using managerially estimated data. Darmon identifies differential skills (potential sales loss when higher performers are replaced by low performers) as the largest cost component. However, because the indirect costs are based on managers' subjective estimation, this quantification cannot be verified, thus offering limited causal inferences. To address these limitations, we rely on objective sales data and perform our analysis at the customer level, which strengthens the causal inference because we can match and control for customer characteristics.

Organizational behavior research has also investigated the financial impact of turnover and the relationship between employee turnover rates and performance. As a general finding, turnover rates are negatively associated with firm performance (e.g., Kacmar et al. 2006; Shaw, Gupta, and Delery 2005; Subramony and Holtom 2012; Ton and Huckman 2008). However, such literature aggregates the unit of analysis (i.e., store or firm level) and cannot address the causal impact of sales rep departure on individual customers.

Sales rep reassignment research. After a sales rep departs, the firm usually reassigns existing customers to other sales reps (e.g., Bendapudi and Leone 2002; Richardson 1999), either by assigning all of them to one replacement rep or by splitting the customer base of the departing sales rep and assigning customers to multiple replacement reps. We focus on the latter approach, which matches the strategy adopted by the focal firm in our empirical setting. The multiple replacement reps might currently work for the firm or could be new to the firm (new hires). Finding appropriate reassignments is vital for a smooth relationship transition, yet most research in this area is conceptual or anecdotal (e.g., Bendapudi and Leone 2001, 2002). Sales managers seem to assume that effective replacement sales reps should have a similar industry background, as demonstrated in the widespread practice of hiring from competitors (Gardner 2005). They also prefer candidates who have demonstrated high past performance, leading to the practice of reassigning accounts to top performers (Groysberg, Lee, and Abrahams 2010). However, the effectiveness of these customer assignment strategies has not been empirically examined.

Furthermore, sales rep effectiveness literature has uncovered some explanatory variables related to sales rep performance (e.g., Farrell and Hakstian 2001; Weitz, Sujan, and Sujan 1986). Most work in this area has focused on the characteristics of ongoing customer–sales rep relationships (e.g., Farrell and Hakstian 2001; Weitz, Sujan, and Sujan 1986), but sales reps' characteristics (e.g., domain knowledge, selling skills) may matter in relationship transition contexts as well. Ahearne and Lam (2012) even call for more dynamic views of customer–sales rep relationships. Thus, we empirically examine the effectiveness of alternative customer assignment strategies (new hires vs. existing sales reps) and investigate how sales outcomes vary by newly assigned sales reps' observable characteristics (e.g., past performance, similarity to departing sales reps). We summarize these research gaps and our attempts to address them in Table 1.

Quantifying the Causal Effect of Sales Rep Transition on Customer Sales

Research in interorganizational relationships has provided theoretical perspectives on the effect of sales rep transitions on firm performance. That is, interfirm trust and commitment drive strong interfirm relationships, which lead to enhanced sales and profits (Morgan and Hunt 1994; Palmatier et al. 2006). Interfirm trust and commitment also operate at several levels, so Doney and Cannon (1997) and Zaheer, McEvily, and Perrone (1998) consider the firm level (e.g., buyer and seller firms) and the interpersonal level (e.g., sales reps and buying personnel). Fang et al. (2008) identify three levels of trust—firms' mutual trust, agency trust between a firm and its own representatives, and the intraentity trust between firms' representatives (similar to interpersonal trust in Zaheer, McEvily, and Perrone [1998])—and establish the differential influences of these three levels of trust in international joint venture performance.

TABLE 1
Research Gaps and Contributions

	Prior Research	Current Research
Sales Rep Turnover Research		
Focus	Most research has focused on antecedents (e.g., Brown and Peterson 1993; Johnston et al. 1990; Trevor 2001)	The current research focuses on quantifying the economic impact
Level of analysis	Firm- or business unit–level (Subramony and Holtom 2012; Ton and Huckman 2008), regional-level (Richardson 1999), or sales rep–level (Darmon 1990) analyses	Customer-level analysis, which enables us to derive causal inferences by matching and controlling for customer characteristics
Data source	Managerially estimated data (Darmon 1990)	Objective customer-level sales data and objective estimates of the effect of sales rep departures on customer sales
Sales Rep Replacement Research		
Approach	Primarily conceptual or anecdotal (Bendapudi and Leone 2001, 2002)	Empirical analysis
Scope	To recognize the importance of selecting and hiring replacement sales reps (Bendapudi and Leone 2002; Darmon 1990)	To examine and differentiate the effects of customer assignments to new hires versus existing sales reps
Replacement/assignment strategies	Conceptual discussions of the goal of replacement strategies (e.g., increase acceptability of replacement employees; Bendapudi and Leone 2002); no examination of specific replacement strategies (i.e., how to select appropriate replacement reps)	We propose two dimensions to describe assignment strategies—sales reps' performance and similarity—and empirically differentiate the effects of the two dimensions.
Performance outcome	No performance outcomes examined	We investigate how different assignment strategies affect objective sales performance.

Applying the multilevel trust–commitment framework to B2B sales rep departures, we suggest that a sales rep transition as a result of turnover will alter the trust between a buyer and its sales rep, which in turn will cause a change in customer sales. Interpersonal trust between a departing sales rep and buying personnel also tends to be cultivated through multiple interactions over time (Zaheer, McEvily, and Perrone 1998), so it is difficult to replicate quickly by replacement reps. When an equally or a less-qualified sales rep is assigned as the replacement, (s)he cannot achieve the same relational strength with customers immediately. The loss of the long-term contact point thus may lower commitment, trust, reciprocity norms, and exchange efficiency (Palmatier 2008; Zoltners, Sinha, and Lorimer 2011), resulting in decreased sales. Conversely, if the replacement is a highly qualified sales rep, capable of surpassing the relationship quality that the previous sales rep had maintained with customers (Bendapudi and Leone 2002; Darmon 1990), customer sales might increase.

Furthermore, the departing sales reps' ability to exploit customer trust before departure may affect customer sales changes too. In particular, if they are subject to commission-based compensation plans, departing sales reps might leverage the trust they have built up with customers to pull orders from the future and earn a higher commission before they leave (Steenburgh 2008). This borrowing from the future lowers sales levels in the postdeparture periods, assuming customer purchasing needs are stable. However, if departing sales reps have not been able to maintain trusting relationships with their customers, customers may anticipate a more qualified replacement and hold their purchases until the replacement arrives, which could produce a sales increase after the transition. Multilevel trust–commitment theory thus predicts changes in customer sales, according to the capabilities of the departing and replacement sales reps, but few empirical assessments quantify the causal impact of sales rep departure on firm performance. Therefore, we ask,

> RQ_1: To what extent are customer sales affected by sales rep transitions?

Effectiveness of new hires versus existing sales reps as replacements. A replacement rep will likely take over the interpersonal relationship between the buyer and the departed sales rep, in the hope of mitigating any sales loss from the transition or even increasing sales by realizing the additional customer potential. Therefore, the sales changes induced by a transition likely differ according to the identity of the replacement. In particular, several factors may put new hires at a performance disadvantage, relative to existing reps, during sales rep transitions. First, new hires generally have less customer-specific sales competence than existing sales reps. They might gain product and procedural knowledge through training, but they are unlikely to be immediately equipped with an understanding of the firm's customers' unique needs. Second, new hires face higher pressure to prove themselves than existing sales reps; therefore, they are more likely to engage in short-term, sales-oriented behaviors (Boichuk et al. 2014). Such behaviors may have damaging effects on the development of long-term trust with customers. Third, new hires suffer from low agency trust within their own hiring firm (Fang et al. 2008): Relative to existing sales reps, new hires have weaker relationships with peers, sales managers, and other firm functions. Therefore, they may receive less support or resources for their relationship-building activities. In Fang et al.'s (2008) trust–commitment framework, new hires tend to display lower interpersonal and agency trust levels than existing sales reps, suggesting the threat of poorer sales outcomes.

However, new hires also could be at an advantage in some transition situations (Cron 1984; Zoltners and Lorimer 2000). First, if a firm's sales processes change as a result of the transition, new hires recruited for the specific needs of the new business are more competent than existing reps who are accustomed to the old processes. For example, media companies' transition from print-focused to digital-focused media requires sales reps to be equipped with extensive digital knowledge so that they can convey the value of digital media platforms to customers (Sridhar and Sriram 2015). New hires who already have such knowledge may be more effective at earning customer trust than existing sales reps. Second, Zoltners and Lorimer (2000) note that a new sales rep approaches the customer's needs with a fresh perspective, which may reveal some new ways to gain customer trust and increase sales. Third, the greater performance pressures on new hires could encourage them to exert more effort to build trusting relationships with customers (Cron 1984). The reasonable arguments on both sides thus lead us to propose the following research question:

> RQ_{2a}: Are sales rep transitions handled more effectively by new hires or by existing sales reps?

Existing reps' similarity. The similarity of the customer bases maintained by the departing and the existing replacement sales reps should affect the sales changes that result from a sales rep transition. In B2B settings, a sales rep's customer base is a proxy for domain-specific knowledge about the selling situations (Weitz, Sujan, and Sujan 1986). For example, customers from various industries differ in their decision processes, purchasing needs, and buying frequency. When a sales rep previously has worked with customers from a particular industry, that experience offers a good indicator of the rep's knowledge of associated selling situations. Most B2B firms also use the customer's industry as a key segmentation variable, which supports the appropriateness of using the industry composition of the customer base to represent a sales rep's domain knowledge. Accordingly, and in line with the multilevel trust–commitment framework, we predict that similar customer bases maintained by the departing and assigned sales reps help mitigate sales losses because the competency of the newly assigned sales reps is evident and the knowledge transfer is more efficient across these entities with their similar domain knowledge (Argote and Ingram 2000; Lane and Lubatkin 1998). In contrast, if the replacement sales rep is dissimilar to the departing sales rep, (s)he may succeed better with cross-selling by leveraging his or her unique knowledge structure. Therefore, we test empirically whether customer base similarity affects sales changes during transition. Formally,

> RQ_{2b}: Are sales rep transitions handled more effectively by replacement sales reps who have customer bases that are similar or dissimilar to those of departing reps?

Existing reps' selling ability. Prior research has confirmed the crucial role of selling ability for improving selling effectiveness in ongoing relationships (e.g., Baldauf and Cravens 2002; Weitz, Sujan, and Sujan 1986). Because a sales rep's past performance is a good indicator of his or her selling capability (Leigh et al. 2014; Verbeke, Dietz, and Verwaal 2011), we use this proxy for selling ability. Sales reps with high selling ability usually can build strong customer trust—whether through their strong selling skills or enhanced selling activities—relative to average sales reps, which then should lead to better selling performance. However, motivation also can affect customer-specific selling performance (Sabnis et al. 2013), such that a low-performing sales rep might be more motivated to devote effort to serving new accounts and thus could achieve greater trust and higher sales than a more skilled sales rep. Considering these arguments on both sides, we propose the following:

RQ_{2c}: Are sales rep transitions handled more effectively by higher- or lower-performing replacement sales reps?

Data

Empirical Context

We obtained data from a leading U.S.-based distributor of electrical component products. The firm uses a field-based sales force to sell to customers in six industry segments: construction, industrial, utility, commercial and government, original equipment manufacturers, and other. Inexperienced sales reps first serve as inside staff in the sales department for two years, providing administrative support to seasoned sales reps but not actively involved in prospecting or closing sales. Externally hired sales reps must have at least two years' field sales experience. The selling task is individual; each sale is attributed to one sales rep, who receives significant commission-based compensation above the base salary.

We interviewed seven sales managers and the vice president of sales to learn how the firm deals with its sales rep turnover, which is approximately 15%, close to the industry average. Turnover occurs through both termination and voluntary departure, though the firm terminates sales reps mainly before or at the end of their two-year probation period and rarely fires seasoned sales reps. Instead, the firm believes that the commission structures it uses helps retain successful sales reps and incentivizes them to perform.[2] The sales managers also indicated that the firm's relationships with its customers are built and maintained through contacts with sales reps. A noncompete agreement prevents departing sales reps legally from taking any customers with them if they are hired by a competitor.

When a sales rep departs, the regional sales manager reassigns the affected customer accounts to other sales reps, who can be either new hires or existing sales reps. No formal guidelines dictate the account reassignment process. Sales managers might reassign customers to several existing sales reps within the same regional office[3] who likely have the technical know-how required to serve customers. In this case, sales managers attempt to reassign customers to existing sales reps whose customer industry portfolio is similar to that of the departing sales reps or who have demonstrated strong sales performance. To avoid overloading these existing sales reps, sales managers also replace the departing sales rep and hire a new rep who has similar industry exposure and an acceptable performance history. The reassignment and implementation process usually occurs one to four weeks after a departing sales rep informs the firm of the departure decision.

From the human resources department, we obtained identifiers and departure dates for 129 sales reps who left the firm in 2011. We combined this information with customer-level sales transactional records from 2008 to 2013. A single transaction record contains identifiers for the customer, industry, sales region, and sales rep, as well as the invoice date and sales amount. The 830 customers served by the 129 departing sales reps generated an average of $73,206 per year per customer for the firm during 2008–2013. We also obtained data about 1,615 customers who transacted with the firm in the same period and were served by 550 sales reps, all of whom stayed with the firm through 2011. The latter group generated an average of $98,958 per year, per customer. Thus, we have data about customers who experienced sales rep transitions, including information from both before and after the sales rep departure (and reassignment), as well as data about a control group of customers who did not experience any sales rep transition.

Sample

The treatment group includes 830 customers who transacted with the firm during 2008–2013 and experienced a sales rep transition in 2011 (approximate data midpoint). Because we know the exact date of each sales rep's departure, we constructed the predeparture period T1 as one year before that date and the postdeparture period T2 as one year after it. This one-year pre- and postdeparture duration is long enough to absorb any interim customer sales shocks that might occur immediately after the transition (i.e., reassignment can take up to four weeks) and allow the replacement sales rep time to establish stable customer relationships. The effects also were robust across different lengths of the pre- and postdeparture periods.[4] The control group consisted of customers whose sales reps did not depart during T1 or T2 but who engaged in at least one transaction in each period. To create our control group, we drew a stratified random sample of customers from 186 strata, constructed according to 31 sales regions and 6 industry segments. In each stratum, we randomly drew a sample that was approximately twice the size of the treatment group in that same

[2]The company does not proactively fire field sales reps; it relies on its compensation scheme to filter out incompetent sales reps, such that they leave voluntarily because they cannot earn sufficient performance-based income. Thus, as we noted previously, our data involve only voluntary turnover.

[3]Our data show that 96.5% of internal reassignments came from the same sales region.

[4]For example, we shortened the window to two quarters and found a significant sales losses of 35.1% (coefficient = $-.432$, $p < .05$) using a difference-in-differences regression, or 31.3% (coefficient = $-.376$, $p < .10$) using propensity score matching (see the Web Appendix). We also ensured that customers had at least one transaction in both the pre- and postdeparture periods, to confirm the meaningful before/after comparison.

stratum to ensure a sufficiently large sample for the matching estimator, which we present subsequently. The resulting sample included 1,615 control group customers. Thus, our final sample consisted of 2,445 customers: 830 in the treatment group and 1,615 in the control group. These 2,445 customers span 273 branches in 31 regions.

We collapsed invoice-level customer transaction data into two periods, T1 and T2, instead of using a more granular time frame (e.g., monthly, quarterly), for two reasons. First, disaggregation would lead to misrepresentations of sales changes because of the customers' heterogeneous purchase cycles (see Figure 1). Second, multiple-period difference-in-differences specifications suffer from inconsistent standard error estimates as a result of serial correlation, which we address by collapsing the data into the pre- and postdeparture periods (Bertrand, Duflo, and Mullainathan 2004).

Measures

We define our measures in Table 2. The dependent variable $Sales_{it}$ is the natural logarithm of total sales in period t (t = T1, T2); the logarithmic transformation helps reduce the skewness, which is common when sales volume is the dependent variable, and gives us support points in the range ($-\infty$, $+\infty$). In Figure 2, we illustrate how T1 and T2 were constructed. We also include the following covariates to control for endogeneity (which we discuss in more detail in the "Method" subsection): (1) customer relationship tenure, measured as the number of quarters between the first transaction and the end of T1; (2) customer purchase size, reflecting the regional share of customer sales; (3) sales rep tenure, or the number of quarters between a sales rep's first transaction to the end of T1; (4) sales rep performance, according to the sales rep's regional sales share; (5) three customer sales trajectory variables that reflect the changes between different quarters of T1 (customer sales change 1 = log of Q2 sales − log of Q1 sales, customer sales change 2 = log of Q3 sales − log of Q2 sales, and customer sales change 3 = log of Q4 sales − log of Q3 sales); (6) sales rep performance trend, or the change in sales reps' regional sales shares from 2009 to 2010; (7) customer industry dummies; (8) branch dummies; and (9) departure quarter dummies.

Descriptive Statistics and Model-Free Evidence

Table 3 contains descriptive statistics for the measures. As Table 4 shows, the treatment and control groups are similar in their industry composition. Table 5 then shows the mean

FIGURE 1
Examples of Customer Monthly Purchasing Patterns, Showing Great Heterogeneity

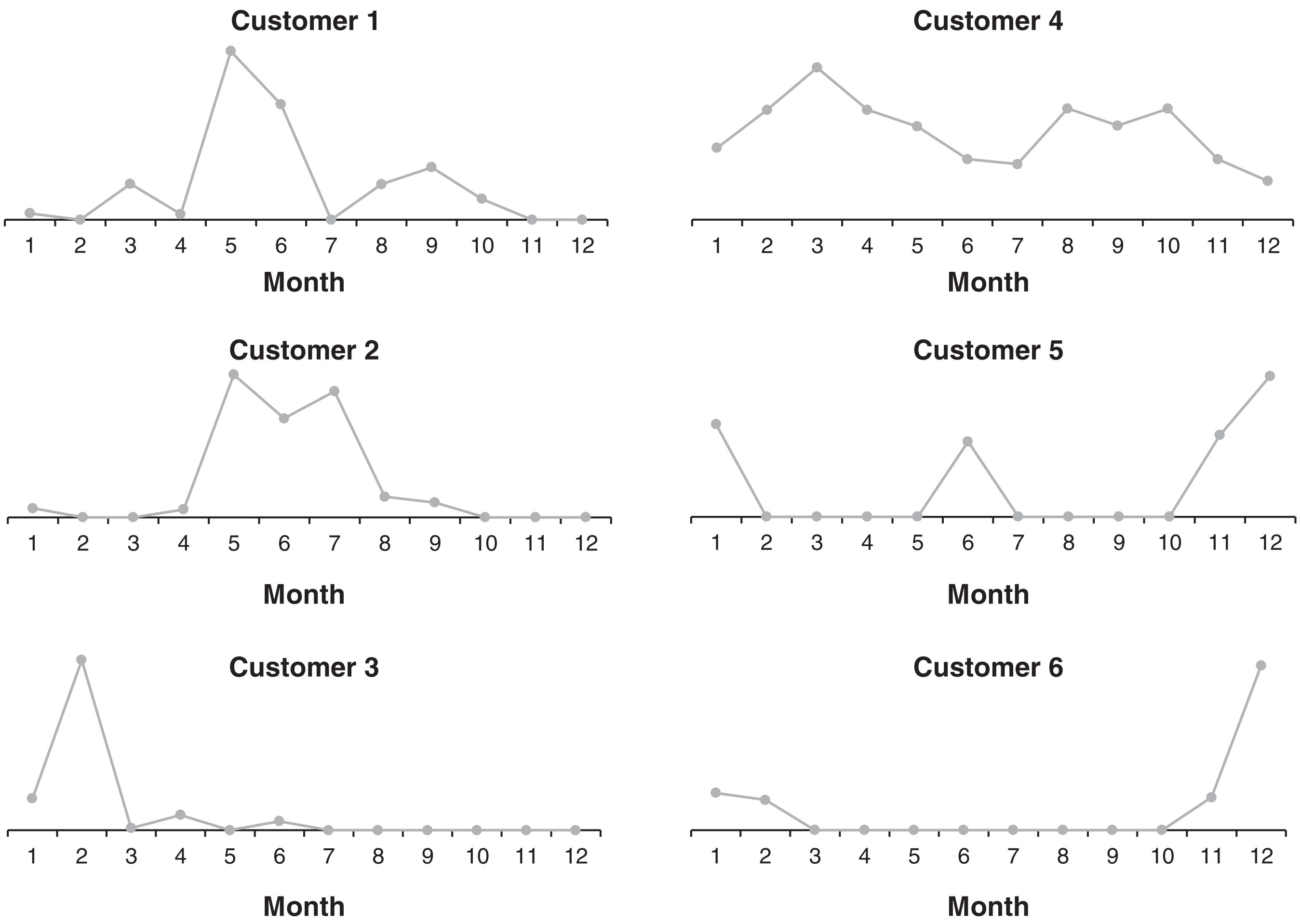


TABLE 2
Variable Descriptions

Variables	Description
Sales	Natural logarithm of total customer sales in period t (t = T1, T2)
Customer Relationship Tenure[a]	The number of quarters since the first transaction to the end of T1
Customer Purchase Size	Regional share of customer sales in 2009, calculated as total sales to a customer in 2009 divided by the total annual sales in the region in which the customer is located
Sales Rep Tenure[b]	Number of quarters from the sales rep's first transaction in the data to the end of T1
Sales Rep Performance[c]	Sales rep's (treatment group's departing sales reps and control group's sales reps) regional sales share in 2009, calculated as the sales rep's annual sales divided by the total annual sales in the region in which the sales rep is located
Customer Sales Change 1	Sales change between the first and second quarters of T1 (log sales of Q2 – log sales of Q1)
Customer Sales Change 2	Sales change between the second and third quarters of T1 (log sales of Q3 – log sales of Q2)
Customer Sales Change 3	Sales change between the third and fourth quarters of T1 (log sales of Q4 – log sales of Q3).
Sales Rep Performance Trend	Change of sales reps' (treatment group's departing sales reps and control group's sales reps) regional sales share from 2009 to 2010.

[a]A customer's first successful transaction can be tracked to January 1, 2006.
[b]A sales rep's first successful transaction can be tracked to April 1, 2008. When we used discretized measures (≤4 quarters, 4–8 quarters, >8 quarters), the results in our model estimations remained similar.
[c]We did not use sales rep sales performance measures in 2010 or afterward, to avoid potential simultaneity issues when the explanatory variables (i.e., sales performance) are constructed by dependent variables (i.e., customer sales).

differences in the covariates between the control and treatment groups in T1. The standardized mean differences of all variables fall below the threshold of .25, indicating a good balance between the two groups (Ho et al. 2007).

As we have mentioned, we included a sales rep's past sales performance and selling tenure as covariates of customer sales to control for nonrandomness in sales rep departure. We reveal that these covariates are associated with declines in customer sales, indicating the face validity of their selection (see the Web Appendix). Table 6 also contains the definitions and descriptive statistics for the similarity between a departing and an existing sales rep and the past performance of the existing sales rep. These statistics are based on the subgroup of customers assigned to existing sales reps in the treatment group.

To obtain model-free evidence, we first compare the sales trends of the treatment and control groups. As Figure 3 shows, the mean sales for the treatment group (natural logs) in the predeparture period (T1) is 10.59, higher than the 10.42 value in the postdeparture period (T2), which is a statistically significant difference (t = 2.59). For the control group, sales in T1 and T2 were 10.41 and 10.44, respectively, so the difference was not significant (t = .50). That is, customers who experienced a sales rep transition exhibited a downward sales trend. When we shortened the window to two quarters before and after departure, the sales trend patterns were similar (t-test statistics are reported in Web Appendix).[5]

[5]In Figure 3, we also provide the purchase frequency (number of transactions) difference between the treatment and control groups. The treatment group shows a significant loss in transaction frequency, from 10.57 in T1 to 9.75 in T2 (t = 2.10); the control group shows significant growth, from 11.42 to 12.58 (t = 3.13). Thus, the treatment group also exhibits decreased purchase frequency after a sales rep departure.

Method

Empirical Strategy to Estimate Causal Effects

To estimate the causal effect of a sales rep transition on customer sales, an ideal experiment would feature an event in which a randomly selected sales rep departs from the firm and a randomly assigned sales rep fills the void. In reality, however, sales rep departures tend to be nonrandom, such that a rep may leave for reasons related to his or her performance; moreover, replacement processes also are nonrandom because managers try to reassign customer accounts strategically. Therefore, to approximate the ideal experiment, we use a difference-in-differences estimate of a customer's sales change, assuming random departure and assignment (vs. before departure), which we compare with the change in sales of a similar customer who does not experience a transition. To augment the specification, we also control for the nonrandomness of sales rep departure and account for nonrandomness in the sales rep replacement decision.

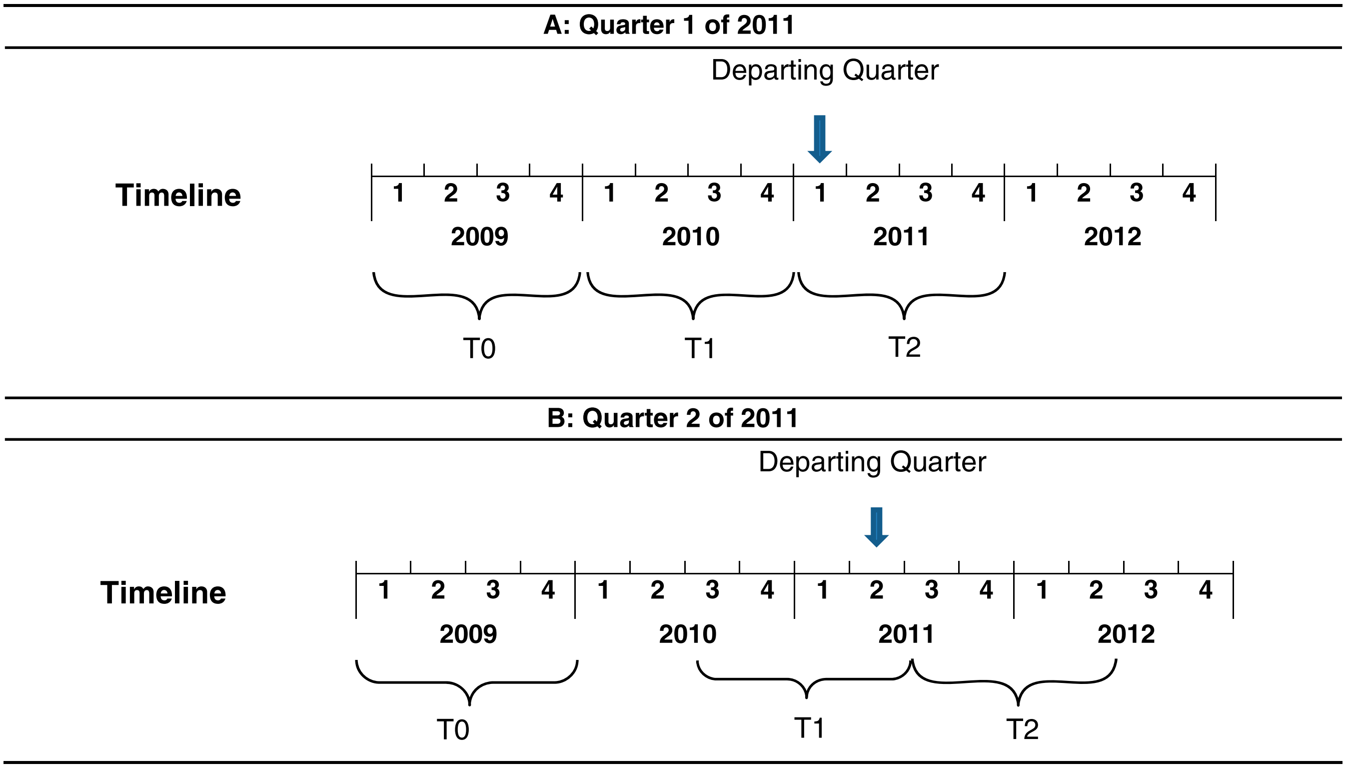
Difference-in-Differences Specification

We use a two-period, difference-in-differences specification to mimic the experimental ideal:

$$\text{(1)} \quad \text{Sales}_{it} = \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 \text{Post\_Period}_t + \beta_3 \text{Treatment}_i \times \text{Post\_Period}_t + \epsilon_{it},$$

where the subscript i pertains to a customer, and the subscript t refers to the period (predeparture period T1 or postdeparture period T2); Sales_{it} is the log-transformed sales to customer i in period t; Treatment_i is the treatment group dummy that equals 1 if customer i is in the treatment group and 0 otherwise; Post_Period_t is the pre–post dummy that equals 1 if t is in T2 and 0 if it is in T1; and ϵ_{it} is a random error term. The coefficient

FIGURE 2
Temporal Illustration for Key Variable Construction



Notes: Panel A shows that if the departing quarter is quarter 1 of 2011, we construct the predeparture period T1 from quarter 1 of 2010 to quarter 4 of 2010 and the postdeparture period T2 from quarter 1 of 2011 to quarter 4 of 2011. This construction is similar to Manchanda, Packard, and Pattabhiramaiah (2015). To construct sales-based covariates such as customer purchase size and sales rep performance, we rely on sales data in T0, which does not overlap with T1 or T2, such that we avoid using the dependent variable (i.e., customer sales) to construct the explanatory variables (i.e., customer purchase size).

β_0 measures average sales from the control group in the predeparture period, β_1 indicates the group mean difference of sales between the treatment and control groups, β_2 reveals the mean difference of sales in T2 relative to T1, and β_3 measures the causal effect of the sales rep transition. Equation 1 also controls for average sales trends and stable customer characteristics that may differ across groups.

Controlling for Nonrandomness in Sales Rep Departure

There are three main sources of nonrandomness in a sales rep's departure decision. First, sales reps may leave for past performance reasons (e.g., Jackofsky 1984; Johnston et al. 1990). The poorest performers likely experience negative job satisfaction or low compensation; the best performers instead may be attracted to superior external career opportunities. A sales rep's job satisfaction and market value are not observable (part of ϵ_{it}) but contribute to the treatment (i.e., departure), so failing to control for them would induce a correlation between the treatment and ϵ_{it} and bias the treatment effect. However, after controlling for sales reps' past performance, their job satisfaction and market value should be distributed randomly. Therefore, we added covariates related to a sales rep's past sales performance and tenure (Cotton and Tuttle 1986) to control for this source of nonrandomness. We also include sales reps' past performance trends, which may correlate with their expectations about their future overall performance.[6]

Second, expected future performance is another predictor of sales rep turnover (Pilling and Henson 1996). Sales reps may leave if they anticipate low purchasing potential among their customers, which would lead to low commissions. The forecast of these future sales again is not observed and could bias the treatment effect, so we enrich our model with customer characteristics, including past purchase sizes, relationship tenure with the firm, and customer sales trajectory in the predeparture period. To the extent that customers' purchasing timing exhibits cyclical patterns across industries, we also add quarter fixed effects. These variables capture information that sales reps use to form their expectations of customers' purchasing power in the future. Conditional on these variables, forecasts of a customer's future sales should be distributed randomly across sales reps.

Third, sales reps may leave for unobserved, sales branch–specific reasons. For example, sales reps may be dissatisfied with the sales branch manager's supervisory ability or branch rules. This variable is part of ϵ_{it} in Equation 1 and may cause correlation between the treatment and ϵ_{it}. To account for this source of nonrandomness, we include branch fixed effects. Accordingly,

[6]We also include the volatility of customer sales to control for sales reps' nonrandom departure decisions in our robustness analyses (see the "Additional Robustness Tests" subsection).

TABLE 3
Correlation and Descriptive Statistics

Variables	1	2	3	4	5	6	7	8	9
	Correlations								
1. Sales (log of sales)	1.00								
2. Customer Relationship Tenure (quarters)	.18	1.00							
3. Customer Purchase Size (%)	.19	.14	1.00						
4. Sales Rep Performance (%)	.12	.11	.65	1.00					
5. Sales Rep Tenure (quarters)	.09	.34	.07	.27	1.00				
6. Customer Sales Change 1	.03	−.09	.00	.02	−.03	1.00			
7. Customer Sales Change 2	.02	−.10	−.01	−.01	−.04	−.43	1.00		
8. Customer Sales Change 3	.01	−.08	−.02	.01	−.07	−.04	−.43	1.00	
9. Sales Rep Performance Trend	−.04	−.07	−.03	−.20	−.50	.00	.01	.03	1.00
Summary Statistics									
Mean	10.45	14.24	.15	2.65	11.11	.25	.48	.78	1.32
SD	1.43	7.84	.94	4.77	3.70	5.48	5.88	6.08	3.76
Min	8.01	2.00	.00	.00	2.00	−12.98	−12.79	−13.02	−14.44
Max	15.96	24.00	20.28	74.34	15.00	13.00	13.52	13.34	15.08

Notes: Entire sample n = 2,445.

we augment Equation 1 with covariates to control for these three sources of nonrandomness in sales rep departure, such that

$$\text{(2)} \qquad \begin{aligned} \text{Sales}_{it} = {} & \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 \text{Post\_Period}_t \\ & + \beta_3 \text{Treatment}_i \times \text{Post\_Period}_t \\ & + \beta_4 X_{it} + \alpha_i + \epsilon_{it}, \end{aligned}$$

where X_{it} captures the time-invariant and time-variant control variables, including sales reps' past observed sales performance and tenure; idiosyncratic customer characteristics such as size and relationship tenure; the customer sales trajectory (Customer Sales 1, 2, and 3); sales reps' past performance trend; and fixed effects for the industry, branch, and quarter. Finally, α_i is a customer-specific random error that captures unobserved customer-level effects.

Controlling for Nonrandomness in Sales Rep Replacement

As discussed previously, when a sales rep departs, the regional sales manager is responsible for reassigning customer accounts to replacement reps, who could be internal (i.e., existing sales reps) or external (i.e., new hires). This assignment is a strategic choice made by the sales manager, with the intent of limiting any deleterious impact resulting from sales rep departure, and is thus nonrandom.

We account for the nonrandomness of assignments (existing sales reps vs. new hires) that result from unobserved factors by using a two-stage Heckman (1979) correction. In the first stage, we model the choice of replacement sales rep (new hire vs. existing sales rep) according to several drivers of this decision with a probit specification. For identification purposes, the covariate set driving replacement choice needs to contain some variables (i.e., exclusion restrictions) that affect this choice but do not directly affect customer sales. We specify three such exclusion restrictions:

1. *Local unemployment rate*[7]: This variable refers to the county or city where the branch is located, because it may affect the supply and availability of sales reps in external labor markets. If the local unemployment rate is high, sales managers likely can hire replacement sales reps because there is a higher proportion of unutilized workers in the local workforce.[8] However, the local unemployment rate should not affect customer sales directly, because sales in the B2B sector are

TABLE 4
Distribution of Customers by Industries (%)

Industry	Treatment Group	Control Group	z-Statistic
Construction	31.64	30.84	.36
Industrial	31.15	31.20	.03
Utility	16.04	16.02	.01
Government and commercial	6.56	6.39	.98
Original equipment manufacturer	13.62	13.25	.25
Others	.99	2.29	2.56**
N	830	1,615	

**$p < .05$.

[7]We obtained annual unemployment rate data at the county level from the Bureau of Labor Statistics (www.bls.gov) for U.S. branches and at the city level from Statistics Canada (www.statcan.gc.ca) for branches in Canada.

[8]When managers pursue new hires, they seek salespeople with a minimum of two years of experience (in keeping with the company's policy). Thus, the unemployment level in a geographic area two years before the focal decision likely represents a shock to the supply of new hires in the geographic area. Therefore, we tested the robustness of our results to the use of two-, three-, and four-year lagged unemployment rates. All the lagged unemployment rates correlate positively with the new hire dummies, consistent with our theoretical prediction, and the results hold as well (for details, see the Web Appendix).

TABLE 5
Mean Differences Between Control and Treatment Groups in T1 Before Matching

	Control Group		Treatment Group			
	M	SD	M	SD	Mean Difference[a]	Standardized Mean Difference[b]
Sales	10.412	1.455	10.591	1.301	−.180***	−.138
Total Number of Transactions	11.420	30.306	10.576	15.047	.845	.056
Customer Relationship Tenure	13.819	7.936	15.064	7.589	−1.245***	−.164
Customer Purchase Size	.136	.703	.186	1.284	−.05	−.039
Sales Rep Performance	2.746	4.368	2.510	5.495	.236	.043
Sales Rep Tenure	10.993	3.851	11.340	3.378	−.347**	−.103
Customer Sales Change 1	.032	5.345	.688	5.702	−.656***	−.115
Customer Sales Change 2	.545	5.795	.350	6.039	.195	.032
Customer Sales Change 3	1.086	6.184	.192	5.845	.894***	.153
Sales Rep Performance Trend	1.483	3.958	.988	3.292	.495***	.150
Number of observations	1,615		830			

**$p < .05$.
***$p < .01$.
[a]Statistical significance of group mean difference t-test.
[b]Difference in means between the treatment and control groups divided by the standard deviation of the treatment group. Better balance across groups is required if this value is greater than .25 (Ho et al. 2007).

driven mainly by business needs and the selling capability of the incumbent sales force.

2. *Ratio of new hires to existing hires in other branches of the same sales region*: This variable reflects common practices within a sales region. A sales manager likely adopts the prevalent practice in the sales region, but these peer branches' assignment choices do not directly affect sales outcomes for the focal sales manager's branch.
3. *Supply of existing sales reps in the focal branch*: This variable indicates the availability of existing sales reps. With many existing sales reps, sales managers likely assign customers to them, yet the number of existing sales reps should not directly affect sales outcomes for customers in the treatment group, because they are served by just one sales rep each.

Thus, the first-stage selection equation is

$$(3) \qquad \text{NewHire}_{it} = \omega_0 + \omega_1\text{Unemploy} + \omega_2\text{NumExisting} + \omega_3\text{PeerNewHire} + \omega_4\text{X}_{it} + \varepsilon_{it},$$

where NewHire_{it} is a dummy variable (equal to 1 if replacement rep is a new hire, and 0 if replacement rep is an existing sales rep); Unemploy is local unemployment rate; NumExisting represents the number of existing sales reps in the same branch; PeerNewHire is the percentage of assignments to new hires in peer branches of same region; X_{it} is a vector of departing sales rep characteristics and other controls (customer relationship tenure and purchase size; departing sales rep tenure, performance level, and performance trend; customer sales trend variables, industry fixed effects, and quarter fixed effects); and ε_{it} is the error term.

In the second step, we follow a Heckman correction procedure[9] and calculate the inverse Mills ratio (IMR) from the first-stage selection equation, then include it as a covariate in Equation 2 to control statistically for the endogeneity of the sales rep replacement decisions.

[9]Although we follow common practices to identify exclusion restrictions, there is little consensus about how to assess the appropriateness of exclusion restrictions (Certo et al. 2016).

$$(4) \qquad \text{Sales}_{it} = \beta_0 + \beta_1\text{Treatment}_i + \beta_2\text{Post\_Period}_t + \beta_3\text{Treatment}_i \times \text{Post\_Period}_t + \beta_4\text{X}_{it} + \beta_5\text{IMR}_i + \alpha_i + \epsilon_{it},$$

where IMR_i is the IMR obtained from the first-stage selection equation, and β_5 is the coefficient capturing its impact on customer sales.

Results

RQ$_1$: Average Treatment Effects of Sales Rep Transition

Column 1 in Table 7 presents the estimates of the difference-in-differences specification from Equation 1, which does not correct for nonrandomness in departure or replacement. Because we transformed the dependent variable into a logarithmic scale, we report the raw estimates in Table 7 but interpret them in percentage terms. The estimates based on the difference-in-differences estimation without covariates (Equation 1) reveal a significant treatment effect ($\beta_3 = -.193, p < .01$) and a 17.6% sales decrease.[10]

The estimates of the difference-in-differences specification from Equation 2 correct for nonrandomness in departure but not in sales rep replacement. When we include customer characteristics as covariates (Table 7, Column 2), the treatment effect is negative and significant ($\beta_3 = -.193$, $p < .01$). We also add sales rep characteristics (Column 3; $\beta_3 = -.194$, $p < .01$) and predeparture quarterly customer sales changes and sales rep performance trends (Column 4; $\beta_3 = -.194$, $p < .01$), and the results hold, revealing a 17.6% sales decrease.

[10]The estimated treatment effect (−.193) is equivalent to a 17.6% sales loss according to the transformation formula: $e^{(-.193)} - 1 = -.176$, which we apply due to our use of log-transformed sales as outcome variables. We applied the same transformation to translate coefficient estimates into percentage changes.

TABLE 6
Variables and Descriptive Statistics for the Subsample of Existing Sales Reps

Variable Name	Definition	M	SD
Similarity	The similarity between a departing and an existing replacement sales rep is computed as the cosine of the angle of two 6 × 1 vectors. One vector represents the departing sales rep's sales shares in each of six industries; the other vector represents the replacement sales rep's shares in each of six industries. The value is bounded between 0 and 1, where 1 represents matching sales shares across six industries.	.723	.374
Performance	The past performance of an existing sales rep is measured as the regional sales rank in predeparture period (T1). The value is bounded between 0 and 1, where 1 represents the top performer.	.502	.298

Notes: Number of observations = 320.

To estimate the average treatment effect after correcting for nonrandomness in both departure and replacement, we first estimated a probit model for sales rep replacement (Table 8). The dependent variable is equal to 1 if the replacement rep is a new hire and 0 if an existing hire. The predictors of the decisions are our three exclusion restrictions (local unemployment rate, ratio of new hires/existing hires used in other regions, and number of available existing reps in the same branch), together with the covariates pertaining to the customer and sales rep characteristics described in Table 5.

The results in Table 8 show that an increase in the local unemployment rate has a positive impact on the probability of a new hire (relative to an existing hire), even though the coefficient is not statistically significant (coefficient = .008, $p > .10$). The ratio of new to existing hires in peer branches of the same sales region also has a positive impact on the probability of a new hire (coefficient = .300, $p < .01$), so sales managers tend to follow common practices in their sales regions. Finally, the number of available existing sales reps shows a negative impact on the probability of a new hire (coefficient = –.030, $p < .01$), indicating that when sales managers have more existing sales reps within the branch, they use those reps instead hiring new ones. The IMR from this first-stage model in turn enabled us to estimate Equation 4, as we detail in Column 5 of Table 7. The estimate of the treatment effect is significant ($\beta_3 = -.194$, $p < .01$) and represents a 17.6% sales decrease.

Robustness Assessment for RQ_1

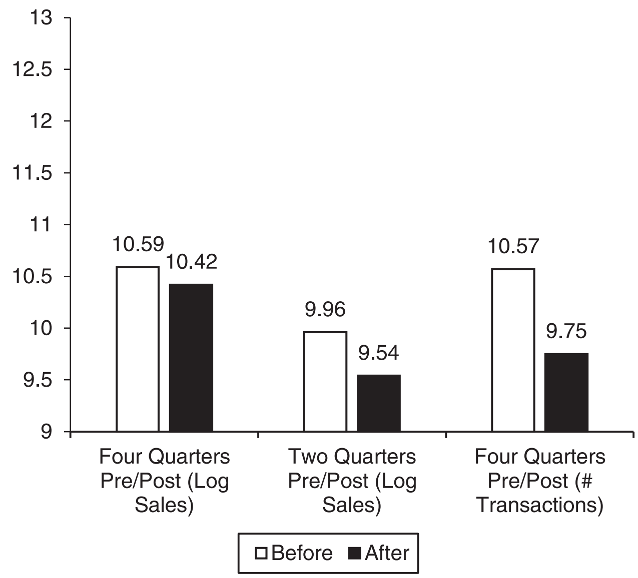
Propensity score matching. We verified the robustness of our results to different estimation strategies by using propensity score matching instead of a regression-based approach. Whereas the regression-based approach conditions all the members of the control and treatment groups using the covariates to obtain the treatment effect, propensity score matching attempts to identify a control group of customers with a similar probability of being selected into the treatment condition; it only compares "similar" pairs of customers in the control and treatment groups who have numerically similar probabilities of receiving the treatment. In the first stage, we obtained a propensity score from a probit model in which we regressed the matching variables on the treatment dummy. We used predeparture sales patterns (four quarters of sales) and customer and sales rep variables (customer relationship tenure, customer purchase size, sales rep performance, sales rep selling tenure, and sales rep performance trend) as matching variables. Then, we compared each customer in the treatment group with a matched customer in the control group on the basis of the proximity of their propensity scores.

To start, we implemented nearest-neighbor matching with replacement, which requires each customer in the treatment group to be paired with the closest match in the control group, according to the value of their propensity scores (Andrews et al. 2015). The treatment effect was negative and significant (coefficient = –.165, $p < .01$), indicating a 15.2% sales loss (Model RR1, Table 9). We replicated these results using both two nearest-neighbors–based matching and kernel matching (Models RR2 and RR3, Table 9). The former compares each customer in the treatment group with the two nearest control group customers; the latter compares every customer in the treatment group with a weighted average of multiple customers in the control group, with weights defined by the propensity score differences between each customer in the control group and the treated customer. We also tested minimum Mahalanobis distance matching, in which each customer in the treatment group is paired with the most similar match according to the Mahalanobis distance of the vectors of characteristic variables (Abadie et al. 2004). This method does not require the same assumptions as propensity score matching (e.g., common support). The results again confirm the significant sales loss from sales rep transition (coefficient = –.141, $p < .05$, or 13.2% sales loss; Model RR4, Table 9). In summary, customer sales losses average 13.2%–17.6% following a sales rep transition, and the estimates differ because of estimation procedures.

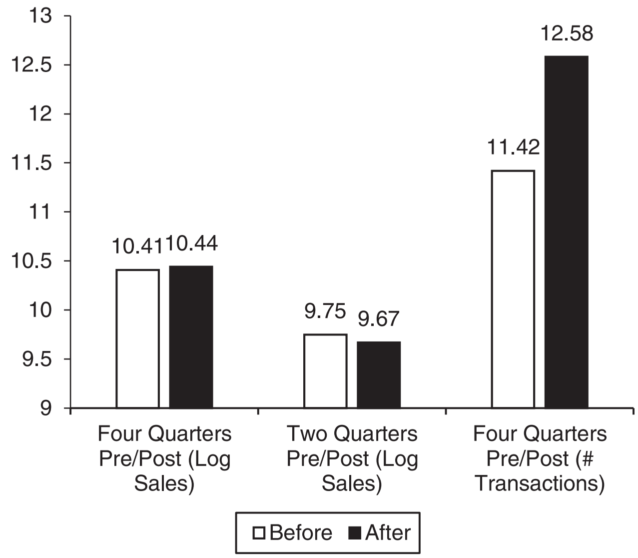
Additional robustness tests. With two sets of additional analyses, we test the robustness of our results to other potential sources of endogeneity. First, departing sales reps may possess private information about future customer sales and make their departure decisions accordingly. To evaluate this endogenous treatment possibility, we include volatility and trends in past customer sales as controls. Conditional on past sales trends, sales volatility captures uncertainty in future sales outcomes. The sales rep is closer to the customer than the firm is, so (s)he also might better understand the reasons for volatility. We use sales volatility as a proxy for the level of private information that sales reps possess. Moreover, a sales rep's departure might be influenced by uncertainty in future sales (Chandrashekaran et al.

FIGURE 3
Differences of Treatment and Control Groups (Model-Free Evidence)

A: Treatment Group (N = 830)



B: Control Group (N = 1,615)



2000). Thus, we include sales past volatility as an additional influence, measured according to the standard deviation of customer quarterly sales in T1. We then estimated a difference-in differences specification (Equation 4) with sales volatility as an additional control variable. The results remained similar (for details, see the Web Appendix).

Second, individual dissimilarity from peers (tenure, age, sex, etc.), group diversity (Jackson et al. 1991; O'Reilly, Caldwell, and Barnett 1989), and peers' turnover (Boles et al. 2012) all could affect turnover decisions. To test for the potential effect of dissimilarity, we conducted another robustness check. Peers are sales reps in the same region. The variables we developed included individual dissimilarity from peers in terms of customer industries, individual dissimilarity from peers in terms of tenure, peer turnover, tenure diversity (i.e., standard deviation of selling tenure of peers), and sales diversity (i.e., standard deviation of sales of peers). None of these variables had significant effects on departure decisions in our sample, and the results remain consistent (for details, see the Web Appendix).

RQ_{2a}: Effectiveness of New Hires Versus Existing Sales Reps as Replacements

The difference-in-differences estimations for the effectiveness questions rely on two subsamples. First, we assess sales to customers who experienced sales rep departure and a new hire replacement, before and after the transition, and these constitute one treatment group. We benchmark the associated change in sales across periods against a control group that did not experience transition. Second, we consider the sales of customers who experienced sales rep departure and an existing hire replacement, before and after the transition, as another treatment group; we benchmark the associated change in sales across periods against a control group that did not experience transition. In each subsample, we control for the nonrandomness in sales rep departure with covariates and for nonrandomness in sales rep replacement using the IMR from the selection equation. Table 10 contains the treatment effects of sales transitions with new hires (Column 1) and existing sales reps (Column 2) as replacements; the results show that new hires as replacements result in a 21.6% (significant) loss in sales (coefficient = −.243, $p < .01$), whereas existing reps as replacements produce an 11.0% statistically nonsignificant loss in sales (coefficient = −.116, $p > .10$).

To confirm this result, we performed matching for each subsample, which helps ensure that the effects of each type of (endogenous) replacement strategy are benchmarked against appropriate control group customers. We report the treatment effects of sales transitions with new hires and existing sales reps as replacements in the Web Appendix. The transitions with new hires result in an 18.5% (significant) loss in sales (coefficient = −.199, $p < .01$), whereas those with existing hires result in a 6.8% statistically nonsignificant loss in sales (coefficient = −.07, $p > .10$).

Thus, sales losses during sales transitions with new hires as replacements are significantly greater than those that occur when existing sales reps are replacements.[11] The "average" existing replacement rep does not produce significant losses in customer sales during the transition. We therefore break down the effects across different types of existing sales reps.

RQ_{2b} and RQ_{2c}: Effectiveness of Existing Reps' Similarity and Past Performance Levels

We estimate Equation 5 for the subsample of transitions involving a replacement by an existing rep:

[11]We also investigated new customer acquisition activities by new hires and existing sales reps in T2. New hires acquired 7.3 customers on average, existing sales reps acquired 11.5 customers, and the difference is statistically significant. Thus, new hires might exhibit poorer new customer acquisition performance than existing sales reps.

TABLE 7
Sales Rep Transition Treatment Effects

Variables	(1) Without Covariates	(2) Customer Characteristics	(3) Sales Rep Characteristics	(4) Predeparture Sales Trend	(5) Heckman Correction
Treatment Dummy	.180*** (.058)	.178** (.071)	.187** (.073)	.196*** (.073)	.193*** (.057)
Post_Period Dummy	.026 (.033)	.022 (.034)	.023 (.034)	.023 (.034)	.023 (.034)
Post_Period Dummy × Treatment Dummy	−.193*** (.053)	−.193*** (.054)	−.194*** (.054)	−.194***,a (.054)	−.194*** (.059)
Customer Relationship Tenure		.029*** (.004)	.029*** (.004)	.033*** (.004)	.033*** (.003)
Customer Purchase Size		.525*** (.115)	.491*** (.115)	.489*** (.118)	.490*** (.118)
Sales Rep Tenure			.002 (.012)	.017 (.015)	.018 (.012)
Sales Rep Selling Performance			.020** (.010)	.020* (.010)	.020* (.012)
Customer Sales Change 1				.019*** (.005)	.019*** (.004)
Customer Sales Change 2				.022*** (.005)	.022*** (.004)
Customer Sales Change 3				.018*** (.005)	.018*** (.004)
Sales Rep Performance Trend				.016 (.011)	.016 (.010)
Constant	10.412*** (.036)	8.808*** (.504)	8.725*** (.521)	8.537*** (.553)	8.453*** (.516)
IMR					−.067 (.089)
Branch Fixed Effects	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sigma_u^2	—	.973	.971	.965	.965
Sigma_e	—	.901	.899	.899	.899
Rho	—	.538	.538	.535	.535
Observations	4,890	4,890	4,890	4,890	4,890
(Adjusted) R-square	.002	.219	.221	.227	.227

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]The treatment effect can be interpreted as follows: a treatment effect of −.194 means that effect size is a −17.6% sales loss using the following transformation formula: $e^{(-.194)} - 1$, owing to our use of log-transformed sales as outcome variables.
Notes: Robust standard errors are in parentheses for Columns 1–4; bootstrapped standard errors are in parentheses in Column 5. For the random-effects model, Sigma_u represents the standard deviation of the random intercept. Sigma_e represents the standard deviation of the error term. Rho represents the explained percentage of the total variance of the random intercept and error term by random intercept (Sigma_u^2)/(Sigma_u^2 + Sigma_e^2).

$$
\begin{aligned}
(5)\quad \text{Sales}_{it} = {} & \beta_0 + \beta_1\text{Treatment} \\
& + \beta_2\text{Post\_Period} + \beta_3\text{Treatment} \times \text{Post\_Period} \\
& + \beta_4\text{Treatment} \times \text{Post\_Period} \times \text{Similarity} \\
& + \beta_5\text{Treatment} \times \text{Post\_Period} \times \text{Performance} \\
& + \beta_6 X_{it} + \beta_7\text{IMR}_i + \alpha_i + \epsilon_{it}.
\end{aligned}
$$

Thus, we modify Equation 4 by including interactions of the treatment effect with Similarity, or customer industry similarity between existing sales reps and departing sales reps, and with Performance, or existing sales reps' past performance level. That is, in Equation 5, we estimate the moderating effects of similarity and past performance using heterogeneous treatment effects.[12]

We computed similarity between a departing and an assigned sales rep in two steps. First, we computed the share of customer sales that the departing and assigned sales reps achieved in each of the six industries, obtaining two 6 × 1 vectors of customer sales shares. Second, we computed the cosine of the angle between the two vectors. A cosine similarity metric is appropriate when each vector component is bounded between 0 and 1, as is the case for the share of customer sales in each industry (Boran and Akay 2014; Hoberg and Phillips 2010). To illustrate, the depicted heterogeneity in selling experience for six representative sales reps in Figure 4 reveals considerable variability: some sales reps sell to only one industry (Sales Rep 3), but others sell to all industries (Sales Rep 6). We computed the past performance of an existing sales rep as the regional sales rank in the predeparture period (T1).

Table 6 provides the relevant definitions and descriptive statistics; the estimates of Equation 5 appear in Table 10 (Column 3). The coefficient of the average treatment effect captured by Treatment × Post_Period is still negative and significant (coefficient = −.285, $p < .05$), the interaction between Similarity and Treatment × Post_Period is positive and significant (coefficient = .359, $p < .05$), and the interaction between

[12]We consider only the interactions of Similarity and Performance with Treatment × Post_Period, because only observations from the treatment group in the postdeparture period vary in these levels. That is, Similarity and Performance matter only when Treatment = 1 and Post_Period = 1. Observations in the control group and in the treatment group in the predeparture period are not assigned to existing sales reps and therefore not affected by their characteristics. This specification is standard in difference-in-differences analyses (e.g., Manchanda, Packard, and Pattabhiramaiah 2015).

TABLE 8
First-Stage Probit Model

Variables	Dependent Variable: New Hire Dummy	
Local Unemployment Rate	.008	(.025)
Number of Existing Sales Reps	–.030***	(.012)
Percentage of Assignments to New Hires in Peer Branches of Same Region	.300**	(.145)
Customer Relationship Tenure	–.004	(.007)
Customer Purchase Size	–.071	(.081)
Sales Rep Tenure	–.086***	(.022)
Sales Rep Performance	.007	(.019)
Customer Sales Change 1	–.013	(.010)
Customer Sales Change 2	–.013	(.010)
Customer Sales Change 3	–.007	(.009)
Sales Rep Performance Trend	–.038**	(.018)
Constant	1.493***	(.365)
Industry Fixed Effects	Yes	
Quarter Fixed Effects	Yes	
Observations	830	
(Adjusted) R-square	.080	

**$p < .05$.
***$p < .01$.

Performance and Treatment × Post_Period is not significant (coefficient = –.182, $p > .10$). According to this pattern, greater similarity between existing and departing sales reps mitigates sales losses from sales rep departure, which provides an answer to RQ_{2b}. Yet existing sales reps' past performance level did not have any significant mitigation effect, which offers a surprising answer to RQ_{2c}. Although we cannot test this assertion, it is possible that low-performing sales reps (who have more slack time than high-performing sales reps) might be more motivated to devote effort to serving new accounts and thus could achieve greater trust and higher sales than more skilled sales reps, who face more severe time and capacity constraints, such that they have little slack time to allocate to their new customers.

We also calculated treatment effects ($\beta_3 + \beta_4 \times$ Similarity + $\beta_5 \times$ Performance) with varying levels of similarity between departing and assigned sales reps, assuming an average past performance level for the assigned rep (.5). Figure 5 shows the point estimates and 95% confidence interval bounds; if similarity is less than .6, the treatment effects are negative and significant. As the similarity level rises, the treatment effects remain negative but become nonsignificant, so high levels of similarity (>.6) can mitigate sales losses from sales rep transition.

Additional Analyses

Long-term effects of assignment. We extended our investigation of the effectiveness of reassignment strategies to a postdeparture period of ten quarters to determine whether the effects evolve over time.[13] If replacement sales reps build relationships with customers, the loss in sales should diminish or even reverse. In Table 11, we present these long-term effects, revealing that customers reassigned to new hires improved their sales more than those reassigned to existing sales reps (9.1% of annual sales compared with 2.2% of annual sales).[14] We still find that a higher level of similarity between existing and departing sales reps leads to better sales outcomes (coefficient = .443, $p < .05$) and that the past performance level of existing sales reps does not have a significant effect on sales outcomes (coefficient = –.153, $p > .10$).

Musical chair effects? Assigning additional customers to existing sales reps might have negative impacts on sales to existing customers. That is, if an existing sales rep suffers time constraints already, any additional tasks could undermine the quality of service (s)he provides to existing customers or the attention (s)he devotes to newly assigned customers. We therefore investigated the potential change in sales to current customers; in Table 12, we show that sales by 107 existing sales reps to 1,258 active customers did not decrease with any statistical significance from T1 (10.46) to T2 (10.45; t = .26). The sales change for customers in the control group was not statistically significant (T1 = 10.41, T2 = 10.44; t = .50), nor was the formal difference-in-differences coefficient (coefficient = –.041, $p > .41$). Thus, assigning additional customers to existing sales reps did not have a negative impact on sales to existing customers, at least within the range of observation for our sample.

Discussion

Some sales rep departure is inevitable; reassigning customers to other sales reps thus is a crucial part of the sales force management process for B2B firms. Using data from a B2B firm, we have evaluated the impact of sales rep transition on customer sales and explored the heterogeneous effects of reassignment strategies. Our difference-in-differences approach causally quantifies the impact of a sales rep's departure on customer sales, such that customer sales drop 13.2%–17.6% one year after the departure. We also exploit the heterogeneity in reassignment decisions to show that customers reassigned to new hires exhibit a 21.6% sales loss, whereas those reassigned to existing sales reps exhibit an 11.0% sales loss. Replacement sales reps with industry experience similar to that of the departing reps appear to have a mitigating effect on sales losses. If the similarity index is above .6 and the replacement sales rep is an average performer, the sales losses could even be eradicated. Over a longer investigation window (i.e., ten quarters), the sales losses among customers served by new hires are also attenuated, so short-term sales losses appear to be due to the learning curve that new hires undergo.

Theoretical Implications

First, our results highlight the causal effects of sales losses from sales force transition, and they have implications for designing customer reassignment strategies after sales rep departure. Our approach and results not only estimate the indirect costs to the firm when sales rep transitions occur but also show that customer reassignment might be managed effectively by using

[13]We adjusted sales in the ten quarters by multiplying them by .4, so the sales magnitude in the postdeparture window was comparable to that in the predeparture window.

[14]The difference between the ten- and four-quarter postdeparture effects were as follows: new hires' performance ([–12.5%] – [–21.6%] = 9.1%) and existing sales reps' performance ([–8.8%] – [–11.0%] = 2.2%).

TABLE 9
Matching Methods

	Propensity Score Matching	Minimum Mahalanobis Distance Matching		
	RR1 Nearest Neighbor (1)	RR2 Nearest Neighbor (2)	RR3 Kernel Matching	RR4 Nearest Neighbor (One Neighbor)
Average treatment effect[a]	–.165***,[b] (.064)	–.133** (.060)	–.167*** (.054)	–.141** (.624)
Observations	2,445	2,445	2,445	2,445

**$p < .05$.
***$p < .01$.
[a]Denotes estimates from propensity score matching methods, calculated on the basis of the weighted difference between the outcome variables of treatment group and matched control group.
[b]To interpret these values, an average treatment effect of –.165 means that effect size is a –15.2% sales loss using the following transformation formula: $e^{(-.165)} - 1$, owing to our use of log-transformed sales as outcome variables.

assigned sales reps' observable characteristics (e.g., industry experience). Accordingly, sales rep management and customer management theories need to move beyond day-to-day management and develop approaches that incorporate the indirect costs of sales rep transitions.

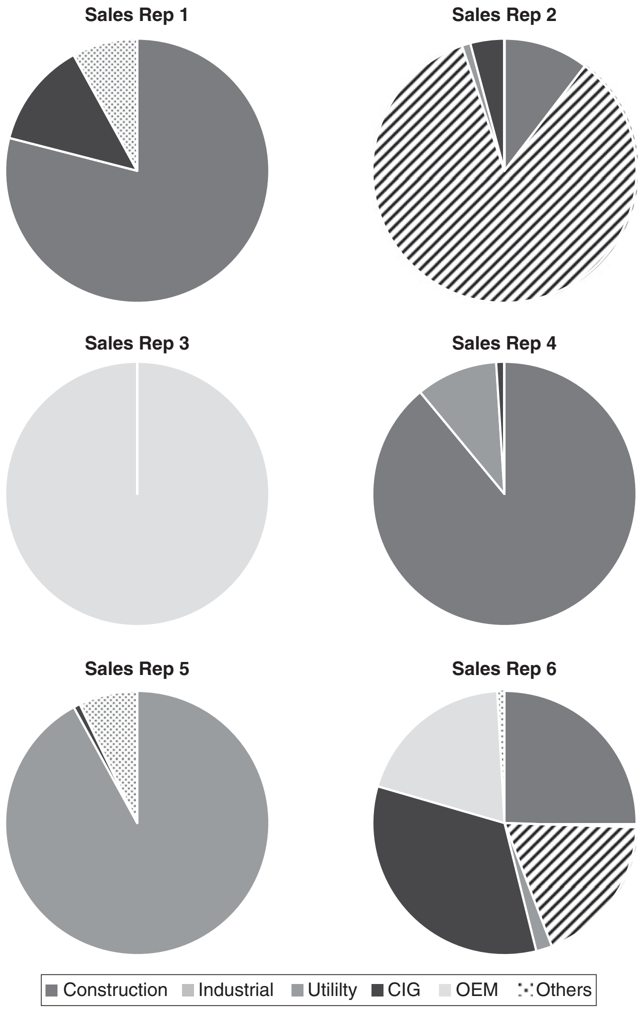
Second, we contribute to relationship marketing and interorganizational relationship literature by quantifying the relationship value generated at the interpersonal level (sales reps and customers). Prior literature has established sales rep–owned loyalty as distinct from firm-owned loyalty (e.g., Kumar, Sunder, and Leone 2014; Palmatier, Scheer, and Steenkamp 2007), with the prediction that the loss of sales rep–owned loyalty may harm customer sales. Our results confirm the existence of this type of loyalty using secondary source data and show that sales rep transitions induce losses in customer sales.

TABLE 10
Assignment Effects (Difference-in-Differences Regression)

	(1)	(2)	(3)
Variables	**New Hire**	**Existing**	**Similarity vs. Performance**
Treatment Dummy	.155 (.096)	–.107 (.111)	.077 (.107)
Post_Period Dummy	.023 (.034)	.024 (.035)	.024 (.035)
DD	–.243*** (.066)	–.116 (.083)	–.285* (.152)
DD × Similarity			.359** (.172)
DD × Performance			–.182 (.220)
Customer Relationship Tenure	.034*** (.004)	.032*** (.004)	.033*** (.004)
Customer Purchase Size	.517*** (.134)	.495*** (.162)	.495*** (.162)
Sales Rep Tenure	.015 (.013)	.017 (.015)	.016 (.015)
Sales Rep Performance	.016 (.012)	.018 (.013)	.017 (.013)
Customer Sales Change 1	.019*** (.005)	.015*** (.005)	.015*** (.005)
Customer Sales Change 2	.023*** (.005)	.019*** (.005)	.020*** (.005)
Customer Sales Change 3	.021*** (.004)	.013*** (.004)	.014*** (.005)
Sales Rep Performance	.009	.008 (.013)	.007 (.013)
Trend	(.012)		
Constant	8.459*** (.517)	8.464*** (.511)	8.424*** (.530)
IMR	.138 (.199)	.188 (.150)	.231 (.153)
Branch Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Sigma_u	.967	.989	.989
Sigma_e	.906	.915	.915
Rho	.533	.539	.539
Observations	4,250	3,870	3,870
(Adjusted) R-square	.242	.247	.247

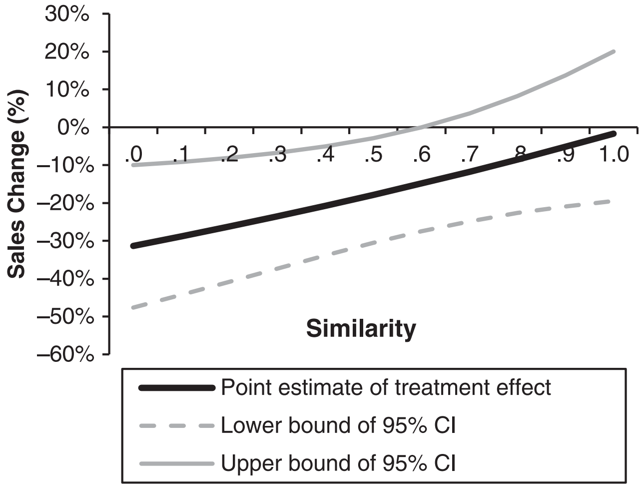
*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: DD = Post_Period Dummy × Treatment Dummy interaction. Bootstrapped standard errors are in parentheses. For the random-effects model, Sigma_u represents the standard deviation of the random intercept. Sigma_e represents the standard deviation of the error term. Rho is the explained percentage of the total variance of the random intercept and error term by random intercept, $(\text{Sigma\_u}^2)/(\text{Sigma\_u}^2 + \text{Sigma\_e}^2)$.

FIGURE 4
Examples of Sales Reps' Selling Industry Experience



Notes: CIG = commercial, industrial, and government; OEM = original equipment manufacturer.

FIGURE 5
Treatment Effects of Similarity (Conditional on Performance = .5)



Notes: This figure shows the treatment effects depending on different levels of similarity between departing and assigned sales reps, conditional on an average past performance level of the assigned sales reps (i.e., .5). The bounds of the 95% confidence interval reveal that if the similarity level is below .6, the treatment effects are negative and significant. As similarity increases, the treatment effects are negative but not significant, so a high level of similarity (>.6) can mitigate the sales losses due to sales rep transitions.

Third, we contribute to sales rep effectiveness literature (Farrell and Hakstian 2001; Weitz, Sujan, and Sujan 1986). Industry experience and performance are both indicators of a sales rep's selling effectiveness, but their effects for mitigating sales losses from sales rep transitions differ: industry experience offers a better indicator of effective loss mitigation than performance. In addition, our finding that sales losses attenuate over time, especially for new hires, underscores the importance of a dynamic view of sales rep effectiveness, which remains underresearched in the sales force performance literature (Ahearne and Lam 2012).

Managerial Implications

Our study is useful for managers who want to evaluate the economic impact of sales rep transitions and improve their customer reassignment practices. First, by estimating the average effects of sales rep transitions on their sales, sales managers can assess the effectiveness of their current reassignment practices. Sales managers in the firm we studied should expect sales rep transitions to lead to losses of $10.65 million–$14.20 million,[15] based on the firm's annual sales of $80.67 million in the predeparture period. Therefore, sales managers can forecast future sales better using predictions of sales reps' departure rate as well as select more effective retention practices.

Second, the heterogeneous effects of reassignment strategies offer insights into how sales managers might adjust their customer reassignment and hiring practices to improve performance. The loss in customer sales that results from transitions can be mitigated by reassigning customers to existing sales reps rather than new hires. The short-term opportunity costs of assigning customers to new hires thus are worth noting, even if new hires can overcome these losses over time. These insights can help sales managers trade off the benefits and costs of reassigning customers to various sales reps.

Third, existing reps differ in their effectiveness as replacement reps. Industry experience similarity between assigned and departing sales reps (but, surprisingly, *not* the sales rep's past performance) has significant loss-mitigating effects. This evidence indicates that domain knowledge similarity is key to managing the relationship transition process. Sales managers should assign customers to sales reps who have industry experience that is similar to the departing rep. The results in our study suggest that when the similarity level is less than .6, the sales losses are significant, but when it is greater than .6

[15]The total sales of the treatment group in T1 were $80.67 million. Estimated sales losses of 13.2%–17.6% (Table 9, Model RR2; Table 8, Column 4) imply sales losses of $10.65–$14.20 million.

TABLE 11
Assignment Effects: Long Term

Variables	(1) New Hire	(2) Existing	(3) Similarity Versus Performance
Treatment Dummy	.106 (.108)	−.107 (.134)	.260** (.119)
Post_Period Dummy	−.179*** (.039)	−.178*** (.039)	.012 (.035)
DD	−.134* (.081)	−.092 (.081)	−.327** (.138)
DD × Similarity			.443** (.176)
DD × Performance			−.154 (.240)
Customer Relationship Tenure	.044*** (.004)	.042*** (.004)	.031*** (.004)
Customer Purchase Size	.497*** (.114)	.485*** (.151)	.475*** (.161)
Sales Rep Tenure	.008 (.015)	.009 (.016)	.009 (.016)
Sales Rep Performance	.015 (.013)	.014 (.014)	.018 (.016)
Customer Sales Change 1	.016*** (.005)	.010* (.006)	.010* (.006)
Customer Sales Change 2	.023*** (.006)	.016** (.006)	.015** (.005)
Customer Sales Change 3	.016*** (.004)	.007*** (.005)	.011** (.005)
Sales Rep Performance Trend	.014 (.013)	.011 (.014)	.012 (.014)
Constant	7.002*** (.457)	6.999*** (.434)	8.553*** (.501)
IMR	.098 (.214)	.104 (.213)	−.186 (.202)
Branch Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Sigma_u	.952	.971	1.008
Sigma_e	1.010	1.010	.913
Rho	.470	.480	.549
Observations	3,554	3,330	3,870
(Adjusted) R-square	.260	.263	.250

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: DD = Post_Period Dummy × Treatment Dummy interaction. Bootstrapped standard errors are in parentheses. For the random-effects model, Sigma_u represents the standard deviation of the random intercept. Sigma_e represents the standard deviation of the error term. Rho is the explained percentage of the total variance of the random intercept and error term by random intercept, $(\text{Sigma\_u}^2)/(\text{Sigma\_u}^2 + \text{Sigma\_e}^2)$.

(keeping the performance level constant), sales losses become nonsignificant and approach zero.

Limitations, Generalizability, and Further Research

This study relies on data from one large B2B distributor. The methods can be applied readily to other sales organizations with similar data, but applying the proposed approach to other selling situations requires some adaptation. For example, our approach might be extended to three other contexts, which suggests ideas for further research. First, “one-to-one” account reassignment could be an alternative strategy, such that all customers of a departing sales rep are assigned to a single replacement, rather than to multiple sales reps, as in our study context. Greater customer heterogeneity (e.g., dispersed geographic locations) may make it cost effective to assign a group of similar customers to one replacement sales rep.[16] The approach of quantifying customer-level sales changes following a sales rep transition still should apply to the one-to-one reassignment strategy, as a special case of the strategy we investigate. However, it also suggests a research opportunity to study sales changes at the sales rep level, which might reveal how the single replacement sales rep’s characteristics affect performance within the departing sales rep’s customer portfolio. A new hire case is similar to what we have studied; an existing rep reassignment raises new questions about how the existing rep can handle the spike in the number of customer accounts.

Second, in our study’s empirical context, customers are mainly served by one key contact sales rep. For team selling contexts, our method can be modified to account for the team characteristics related to a sales rep’s departure decision and the replacement decision. For example, individual dissimilarity from team peers, team diversity, and peers’ turnover might be significant predictors of individual turnover decisions, and the replacement’s similarity with team peers or adaptiveness to new teams might be factors that managers should consider when choosing replacement sales reps. Further research could incorporate these variables into our proposed approach and thereby correct for endogenous departure and replacement decisions.

Third, cross-selling is another important B2B selling context that research could investigate. How does sales rep transition affect cross-selling performance? A modified version of our approach could include cross-selling sales volume as an outcome variable and also control for sales reps’ cross-selling ability. In a team selling context, researchers also might incorporate team-level cross-selling characteristics and identify how a change for an individual member (i.e., departure and arrival of team members) affects cross-selling functions.

[16]When service areas are dispersed and discontinuous, it is not feasible to assign customers in one area to sales reps in other areas because of the long travel distance. A common practice thus is to assign all customers of a departing sales rep to a new hire or to another existing sales rep who works in the same area.

TABLE 12
Sales Comparison of Existing Sales Reps' Customers Versus Control Group

Four Quarters Pre- and Postdeparture	N	T1 Predeparture	T2 Postdeparture	Difference T2 − T1
Existing sales reps' customers	1,258	10.46	10.45	−.01 (.26)
Control group	1,615	10.41	10.44	.03 (.50)
Difference of differences[a]				−.04 (.86)

[a]The difference in T1 to T2 sales changes of the two groups was −.04, which was not statistically significant.
Notes: t-values are in parentheses. We investigated the change in sales from current customers of existing sales reps (i.e., non–new hire) to address the concern that sales reps may be distracted by newly assigned customers because they already have an established customer base. The 107 existing sales reps had 1,258 active customers, whose sales in T1 and T2 did not change significantly. We ran the augmented difference-in-differences specification in Equation 2 by considering the customers served by existing sales reps in T1 as treatment group. The treatment effect is a 4.0% sales decrease (coefficient = −.041, $p > .41$), which was not statistically significant.

Our study also has a few other limitations. We consider voluntary sales rep departure, which reflects the situation in our study context. However, sales reps who leave involuntarily may exhibit different behaviors depending on how firms handle their dismissal. It would be worthwhile to study whether the form of the sales rep's departure (voluntary vs. involuntary) affects firm–customer relationships and customer sales. For example, departing sales reps might leave voluntarily in response to the private information they have about future sales trends, which we addressed by assuming that future sales were a function of past sales in our analysis. Yet further research might use exit survey data to address this question more directly. Our study also does not account for differences in new hires' past industry experience or selling performance; additional research could quantify the trade-offs in these background variables for new hires. Finally, a true test-and-control experiment might provide more definitive answers to our research questions than are possible with our quasi-experimental analysis. Even with these caveats, we hope our work stimulates more research in this area that can continue to provide useful insights and guidelines for sales managers faced with the constant challenge of reassigning customer accounts after a sales rep leaves.

REFERENCES

Abadie, Alberto, David Drukker, Jane L. Herr, and Guido W. Imbens (2004), "Implementing Matching Estimators for Average Treatment Effects in Stata," *Stata Journal*, 4 (3), 290–311.

Ahearne, Michael, and Son K. Lam (2012), "Sales Force Performance: A Typology and Future Research Priorities," in *Handbook on Business to Business Marketing*, Gary L. Lilien and Rajdeep Grewal, eds. Cheltenham, UK: Edward Elgar Publishing, 496–520.

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

Andrews, Michelle, Xueming Luo, Zheng Fang, and Anindya Ghose (2015), "Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness," *Marketing Science*, 35 (2), 218–33.

Argote, Linda, and Paul Ingram (2000), "Knowledge Transfer: A Basis for Competitive Advantage in Firms," *Organizational Behavior and Human Decision Processes*, 82 (1), 150–69.

Baldauf, Artur, and David W. Cravens (2002), "The Effect of Moderators on Salesperson Behavior and Salesperson Outcome Performance and Sales Organization Effectiveness Relationships," *European Journal of Marketing*, 36 (11/12), 1367–88.

Bendapudi, Neeli, and Robert P. Leone (2001), "How to Lose Our Star Performer Without Losing Customers, Too," *Harvard Business Review*, 79 (10), 104–15.

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

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan (2004), "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*, 119 (1), 249–75.

Boichuk, Jeffrey P., Willy Bolander, Zachary R. Hall, Michael Ahearne, William J. Zahn, and Melissa Nieves (2014), "Learned Helplessness Among Newly Hired Salespeople and the Influence of Leadership," *Journal of Marketing*, 78 (January), 95–111.

Boles, James S., George W. Dudley, Vincent Onyemah, Dominique Rouziès, and William A. Weeks (2012), "Sales Force Turnover and Retention: A Research Agenda," *Journal of Personal Selling & Sales Management*, 32 (1), 131–40.

Boran, Fatih Emre, and Diyar Akay (2014), "A Biparametric Similarity Measure on Intuitionistic Fuzzy Sets with Applications to Pattern Recognition," *Information Sciences*, 255, 45–57.

Brown, Steven P., and Robert A. Peterson (1993), "Antecedents and Consequences of Salesperson Job Satisfaction: Meta-Analysis and Assessment of Causal Effects," *Journal of Marketing Research*, 30 (February), 63–77.

Certo, S. Trevis, John R. Busenbark, Hyun-soo Woo, and Matthew Semadeni (2016), "Sample Selection Bias and Heckman Models in Strategic Management Research," *Strategic Management Journal*, 37 (13), 2639–57.

Chandrashekaran, Murali, Kevin McNeilly, Frederick A. Russ, and Detelina Marinova (2000), "From Uncertain Intentions to Actual Behavior: A Threshold Model of Whether and When Salespeople Quit," *Journal of Marketing Research*, 37 (November), 463–79.

Churchill, Gilbert A., Jr., Neil M. Ford, Steven W. Hartley, and Orville C. Walker Jr. (1985), "The Determinants of Salesperson Performance: A Meta-Analysis," *Journal of Marketing Research*, 22 (May), 103–18.

Cotton, John L., and Jeffrey M. Tuttle (1986), "Employee Turnover: A Meta-Analysis and Review with Implications for Research," *Academy of Management Review*, 11 (1), 55–70.

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

Darmon, René Y. (1990), "Identifying Sources of Turnover Costs: A Segmental Approach," *Journal of Marketing*, 54 (April), 46–56.

Doney, Patricia M., and Joseph P. Cannon (1997), "An Examination of the Nature of Trust in Buyer–Seller Relationships," *Journal of Marketing*, 61 (April), 35–51.

Fang, Eric (Er), Robert W. Palmatier, Lisa K. Scheer, and Ning Li (2008), "Trust at Different Organizational Levels," *Journal of Marketing*, 72 (March), 80–98.

Farrell, Seonaid, and A. Ralph Hakstian (2001), "Improving Salesforce Performance: A Meta-Analytic Investigation of the Effectiveness and Utility of Personnel Selection Procedures and Training Interventions," *Psychology and Marketing*, 18 (3), 281–316.

Gardner, Timothy M. (2005), "Interfirm Competition for Human Resources: Evidence from the Software Industry," *Academy of Management Journal*, 48 (2), 237–56.

Groysberg, Boris, Linda-Eling Lee, and Robin Abrahams (2010), "What It Takes to Make Star Hires Pay Off," *MIT Sloan Management Review*, 51 (2), 57–61.

Heckman, James J. (1979), "Sample Selection Bias as a Specification Error," *Econometrica*, 47, 153–62.

Ho, Daniel E., Koosuke Imai, Gary King, and Elizabeth A. Stuart (2007), "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," *Political Analysis*, 15 (3), 199–236.

Hoberg, Gerard, and Gordon Phillips (2010), "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis," *Review of Financial Studies*, 23 (10), 3773–811.

Jackofsky, Ellen F. (1984), "Turnover and Job Performance: An Integrated Process Model," *Academy of Management Review*, 9 (1), 74–83.

Jackson, Susan E., Joan F. Brett, Valerie I. Sessa, Dawn M. Cooper, Johan A. Julin, and Karl Peyronnin (1991), "Some Differences Make a Difference: Individual Dissimilarity and Group Heterogeneity as Correlates of Recruitment, Promotions, and Turnover," *Journal of Applied Psychology*, 76 (5), 675–89.

Johnston, Mark W., A. Parasuraman, Charles M. Futrell, and William C. Black (1990), "A Longitudinal Assessment of the Impact of Selected Organizational Influences on Salespeople's Organizational Commitment During Early Employment," *Journal of Marketing Research*, 27 (August), 333–44.

Kacmar, K. Michele, Martha C. Andrews, David L. Van Rooy, R. Chris Steilberg, and Stephen Cerrone (2006), "Sure Everyone Can Be Replaced … But At What Cost? Turnover as a Predictor of Unit-Level Performance," *Academy of Management Journal*, 49 (1), 133–44.

Kumar, V., Sarang Sunder, and Robert P. Leone (2014), "Measuring and Managing a Salesperson's Future Value to the Firm," *Journal of Marketing Research*, 51 (October), 591–608.

Lane, Peter J., and Michael Lubatkin (1998), "Relative Absorptive Capacity and Interorganizational Learning," *Strategic Management Journal*, 19 (5), 461–77.

Leigh, Thomas W., Thomas E. DeCarlo, David Allbright, and James Lollar (2014), "Salesperson Knowledge Distinctions and Sales Performance," *Journal of Personal Selling & Sales Management*, 34 (2), 123–40.

Manchanda, Puneet, Grant Packard, and Adithya Pattabhiramaiah (2015), "Social Dollars: The Economic Impact of Customer Participation in a Firm-Sponsored Online Customer Community," *Marketing Science*, 34 (3), 367–87.

Morgan, Robert M., and Shelby D. Hunt (1994), "The Commitment-Trust Theory of Relationship Marketing," *Journal of Marketing*, 58 (July), 20–38.

O'Connell, Matthew, and Mei-Chuan Kung (2007), "The Cost of Employee Turnover," *Industrial Management*, 49 (1), 14–19.

O'Reilly, Charles A., III, David F. Caldwell, and William P. Barnett (1989), "Work Group Demography, Social Integration, and Turnover," *Administrative Science Quarterly*, 34 (1), 21–37.

Palmatier, Robert W. (2008), "Interfirm Relational Drivers of Customer Value," *Journal of Marketing*, 72 (July), 76–89.

Palmatier, Robert W., Rajiv P. Dant, Dhruv Grewal, and Kenneth R. Evans (2006), "Factors Influencing the Effectiveness of Relationship Marketing: A Meta-Analysis," *Journal of Marketing*, 70 (October), 136–53.

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

Pilling, Bruce K., and Steve W. Henson (1996), "Employing Dyadic Data to Assess the Accuracy of Salespersons' Perceptions of Their Customers: Antecedents to and Impact on Performance," *Proceedings of the 1996 Academy of Marketing Science (AMS) Annual Conference,* Elizabeth Wilson and Joseph F. Hair Jr., eds. New York: Springer International Publishing, 46–50.

Richardson, Robert (1999), "Measuring the Impact of Turnover on Sales," *Journal of Personal Selling & Sales Management*, 19 (4), 53–66.

Sabnis, Gaurav, Sharmila C. Chatterjee, Rajdeep Grewal, and Gary L. Lilien (2013), "The Sales Lead Black Hole: On Sales Reps' Follow-Up of Marketing Leads," *Journal of Marketing*, 77 (January), 52–67.

Shaw, Jason D., Nina Gupta, and John E. Delery (2005), "Alternative Conceptualizations of the Relationship Between Voluntary Turnover and Organizational Performance," *Academy of Management Journal*, 48 (1), 50–68.

Sridhar, Shrihari, and Srinivasaraghavan Sriram (2015), "Is Online Newspaper Advertising Cannibalizing Print Advertising?" *Quantitative Marketing and Economics*, 13 (4), 283–318.

Steenburgh, Thomas J. (2008), "Effort or Timing: The Effect of Lump-Sum Bonuses," *Quantitative Marketing and Economics*, 6 (3), 235–56.

Subramony, Mahesh, and Brooks C. Holtom (2012), "The Long-Term Influence of Service Employee Attrition on Customer Outcomes and Profits," *Journal of Service Research*, 15 (4), 460–73.

Ton, Zeynep, and Robert S. Huckman (2008), "Managing the Impact of Employee Turnover on Performance: The Role of Process Conformance," *Organization Science*, 19 (1), 56–68.

Trevor, Charlie O. (2001), "Interactions Among Actual Ease-of-Movement Determinants and Job Satisfaction in the Prediction of Voluntary Turnover," *Academy of Management Journal*, 44 (4), 621–38.

U.S. Bureau of Labor Statistics (2013), "Job Openings and Labor Turnover Archived News Releases," (accessed June 8, 2015), http://www.bls.gov/schedule/archives/jolts_nr.htm.

Verbeke, Willem, Bart Dietz, and Ernst Verwaal (2011), "Drivers of Sales Performance: A Contemporary Meta-Analysis. Have Salespeople Become Knowledge Brokers?" *Journal of the Academy of Marketing Science*, 39 (3), 407–28.

Weitz, Barton A., Harish Sujan, and Mita Sujan (1986), "Knowledge, Motivation, and Adaptive Behavior: A Framework for

Improving Selling Effectiveness," *Journal of Marketing*, 50 (October), 174–91.
Zaheer, Akbar, Bill McEvily, and Vincenzo Perrone (1998), "Does Trust Matter? Exploring the Effects of Interorganizational and Interpersonal Trust on Performance," *Organization Science*, 9 (2), 141–59.
Zoltners, Andris A., and Sally E. Lorimer (2000), "Sales Territory Alignment: An Overlooked Productivity Tool," *Journal of Personal Selling & Sales Management*, 20 (3), 139–50.
Zoltners, Andris A., Prabhakant K. Sinha, and Sally E. Lorimer (2011), "Who Owns Your Customer Relationships: Your Salespeople or Your Company?" *Harvard Business Review* (December 21), https://hbr.org/2011/12/who-owns-your-customer-relatio.
Zoltners, Andris A., Prabhakant K. Sinha, and Sally E. Lorimer (2012), "Building a Winning Sales Management Team: A Managerial Perspective," in *Handbook on Business to Business Marketing*, Gary L. Lilien and Rajdeep Grewal, eds. Cheltenham, UK: Edward Elgar Publishing, 521–38.