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Learning from Peers: Knowledge Transfer and Sales Force Productivity Growth

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We study how peers impact worker productivity growth among salespeople in the cosmetics department of a department store. We first exploit a shift assignment policy that creates exogenous variation in salespersons' peers each week to identify and quantify sources of worker learning. We find that peer-based learning is more important than learning-by-doing for individuals, and there is no evidence of forgetting. Working with high-ability peers substantially increases the long-term productivity growth of new salespeople. We then examine possible mechanisms behind peer-based learning by exploiting the multiple colocated firms in our setting that sell products with different task difficulties and compensate their sales forces using either team-based or individual-based compensation systems. The variation in incentives to compete and cooperate within and across firm boundaries, combined with variation in sales difficulty for different product classes, allows us to suggest two mechanisms behind peer-based learning: observing successful sales techniques of peers and direct teaching. Our paper advocates the importance of learning from one another in the workplace and suggests that individual peer-based learning is a foundation of both organizational learning curves and knowledge spillovers across firms.

Keywords: sales management; sales force; personal selling; retailing; social interactions; knowledge transfer; learning models; social learning; peer-based learning
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1. Introduction

A well-developed literature in economics and management studies learning curves at the group and organizational level. The primary focus of the research has been on identifying learning-by-doing through cost decreases with cumulative production (Arrow 1962, Argote and Epple 1990, Thompson 2001), as well as organizational forgetting in periods of low production (Darr et al. 1995, Benkard 2000, Thompson 2007). We have little evidence, however, of the underlying individual mechanisms that generate this phenomenon (Adler and Clark 1991). Although individual learning-by-doing through experimentation and observation of own outcomes is a common explanation for productivity growth (Blume and Franco 2007), social learning theory suggests peers may also play a critical role (Ellison and Fudenberg 1993, Bala and Goyal 1998, Young 2009). This peer-based learning can involve both observing peers' practices and active teaching by peers (Arrow 1994). Despite evidence of peer-based learning in education (Sacerdote 2001), crime (Bayer et al. 2009), healthcare (KC et al. 2013), and economic development (Bandiera and Rasul 2006), direct evidence in commercial and industrial settings is rare.

In this paper we dissect the separate roles of peer-based learning and individual learning-by-doing (and forgetting) in the productivity change of salespeople, with learning from peers as our primary focus. We also extend this focus to study peer-based learning across firm boundaries, motivated by more macro-level evidence of knowledge transfer across firms (Argote et al. 1990), store locations (Darr et al. 1995), and work shifts (Epple et al. 1996). Exploiting firm boundaries also helps disentangle the mechanisms that might drive peer-based learning. Our empirical setting is four years of individual sales data for 92 salespeople working at 11 colocated cosmetics counters in a department store. This research setting matches our research agenda because multiple cosmetics manufacturers employ salespeople at counters on the same retail floor, allowing us to observe peer-based learning both within and across firms. More importantly, the difficult task of selling

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cosmetics products with often unobservable quality makes learning from peers critical for productivity growth.

We conceptualize the sales task in the cosmetics counters as a stochastic production function with parameters linking output (sales) with input (selling activities) variables. Salespeople have heterogeneous selling abilities based on different knowledge levels of these parameters, which in turn translate into unique individual sales productivities.[1] The parameters are particularly unknown to new salespeople, who must learn their values to increase sales. Although these values could in principle be learned by experimenting with inputs and observing outcomes (Easley and Kiefer 1988), such a learning-by-doing process is likely to be slow in our setting because selling cosmetics products involves high-dimensional parameters. Furthermore, the short-term cost of failure (i.e., lost sales commissions) may dissuade salespeople from experimenting with inputs. We argue that a more effective learning strategy is to observe peers and to seek their instruction on the optimal activities, i.e., learning from peers.

To identify peer-based learning, we exploit the store's pseudo-random worker shift assignment, which creates exogenous changes in the weekly pool of a given salesperson's peers. This primary variation of shift assignment is complemented by other shocks, including leaves of absence and a counter relocation. These exogenous peer variations help address potential concerns of strategic worker assignment, reflection, and mean reversion. Based on these data features, we first use a regression that specifically controls for both firms selecting salespeople based on initial ability and learning potential of newly hired salespeople to show evidence of new salespeople learning from high-ability peers, within and across counters. We then build a more comprehensive model allowing a salesperson's selling ability in any period to depend on knowledge accumulated from past interaction with peers, learning-by-doing, and forgetting.

Our estimation results show that learning from peers at the same and adjacent counters is critical to the productivity growth of new salespeople. Learning-by-doing plays a lesser role, and forgetting is insignificant. A new salesperson working alone for 40 hours in her first week would improve her future sales by 2%. If she were to work constantly with a within-counter peer of twice her ability, her sales productivity would grow by an additional 5% to 6% in the next week. A simultaneously staffed peer of twice her ability at an adjacent competing counter would generate an additional productivity growth of 1% to 1.5%.

The existence of firm boundaries, different product types, and various compensation systems in our setting allows us to illustrate and dissect two mechanisms of peer-based learning. Although some knowledge may be learned through direct observation, products that are more difficult to sell may require active teaching from peers, a process unlikely across firm boundaries because of incentives to compete. Specifically, we compare the peer-based learning of salespeople when selling two product subcategories of different task difficulty—skin care and makeup. Skin care products, as credence goods (Darby and Karni 1973), are more difficult to sell than makeup products, for which efficacy is immediately visible. We find that for skin care products, cross-counter learning is far weaker than learning from within-counter peers, whereas for makeup products the two effects are similar. We argue that salespeople can learn from observing simpler tasks, thereby making cross-counter peers viable knowledge sources. Teaching from within-counter peers is essential for more complicated tasks. We also find that salespeople at individual-based counters learn more from cross-counter peers than their team-based peers, suggesting that financial incentives may induce salespeople to invest different levels of time and effort toward active learning.

We examine alternative explanations for our model estimates, including customer loyalty, peer effects in work ethic, mean reversion, and data aggregation issues, and we present evidence that these alternative hypotheses cannot explain our results. We also conduct interviews with department store salespeople in both China and the United States, which provide further evidence validating the learning mechanisms that we argue. Finally, we conduct two counterfactual experiments to demonstrate the economic value of retaining star salespeople and maintaining team heterogeneity in worker shift assignments, both generated from enhancing peer-based learning for newly hired salespeople.

The peer-based learning investigated in this study substantially differs from the "peer effect" identified in previous work (e.g., Mas and Moretti 2009, Nair et al. 2010, Chan et al. 2014). Chan et al. (2014) use a data set from the same source to investigate how compensation impacts peer effects, but they only examine the *contemporaneous* effect of peers on a salesperson's sales, assuming that the salesperson's ability is stable over time. In contrast, this study focuses on how peer-based learning helps increase *ability*. Peers thus have a long-term impact on worker productivity not observed in previous peer effect studies. Furthermore, our results show that although competing

[1] Throughout this paper we use "ability" to refer to a salesperson's level of knowledge of the sales task (which we estimate) and "productivity" to refer to the salesperson's output level (measured by sales revenue).

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with high-ability peers can have an immediate negative impact on sales (Chan et al. 2014), these same high-ability competitors can provide future benefits to a new salesperson's sales through learning. This study, therefore, complements the previous work on peer effects and helps offer a more complete picture of the dynamics of workplace interaction. This study also suggests that the cohort effects observed in education (e.g., Black et al. 2013) may have widespread parallels in commercial and industrial settings. The challenge to estimating this learning effect is that the contemporaneous peer effect will be accumulated as "human capital" that influences future sales. Consequently, we must rely on a new identification and estimation strategy that is also different from the previous peer effect studies.

This study has important implications for the marketing literature on learning and sales force management. Whereas the marketing literature on learning focuses on consumer or customer learning on brand attributes and product quality (e.g., Meyer and Sathi 1985, Erdem and Keane 1996, Erdem 1998, Villas-Boas 2004, Narayanan and Manchanda 2009, Chintagunta et al. 2012), we show that learning is also highly important in those who *serve* consumers, and peer-based learning is a critical source of learning among salespeople. The few economics and marketing papers on learning from others have all focused on consumers (Cai et al. 2009, Ching 2010, Zhang 2010). Furthermore, because these papers have primarily assumed that consumers can observe others' choices (e.g., where they eat) but not the outcomes of those choices (e.g., their satisfaction with the meal), the estimated learning effects could be spuriously overstated (Shin et al. 2012). In our setting, salespeople observe both peers' inputs (i.e., sales efforts) and the corresponding outputs (i.e., sales), and hence we are able to make a more direct and cleaner inference on learning from others.[2] Moreover, our paper is the first (to our knowledge) in economics, marketing, or management to empirically deconstruct organizational learning to both individual experience-based and peer-based processes.[3]

Sales forces are undoubtedly critical components of marketing in both business-to-consumer and business-to-business environments (Kotler and Keller 2008). With three times the amount spent on sales forces as on advertising (Zoltners et al. 2008), and with more than 20 million Americans (Albers et al. 2008) and 65 million Chinese employed as salespeople (National Bureau of Statistics of China 2010), improving the sales force productivity is critical for managers. Most studies of sales force management assume independence among salespeople (e.g., Basu et al. 1985, Mantrala et al. 1994, Joseph and Kalwani 1995, Godes 2003, Misra et al. 2005, Caldieraro and Coughlan 2009, Misra and Nair 2011, Chung et al. 2014).[4] However, as Mantrala et al. (2010) explain, we know little about how worker interactions such as knowledge sharing impact productivity. Our results suggest that in settings where salespeople are colocated (e.g., department store) or compete for the same customers (e.g., pharmaceutical sales), they can significantly influence one another's long-term productivity. Consequently, team heterogeneity and turnover both have persistent impacts on firm performance.

The structure of the rest of this paper is as follows. Section 2 discusses the empirical setting. Section 3 conceptualizes salesperson learning from experience and peers. Section 4 presents initial evidence supporting peer-based learning and our identification conditions. Section 5 develops a comprehensive empirical model of salesperson learning. Section 6 presents the estimation results and discusses the underlying mechanisms of our findings of peer-based learning. Section 7 concludes.

2. Empirical Setting

Our empirical setting is cosmetic sales in a department store in a large metropolitan area in China. This department store is one of the largest in China in both sales and profit and has 15 major brands in its cosmetics department. Each of the brands occupies a counter on the same floor and hires their own salespeople to promote and sell its products, while paying the department store a share of their revenues. The cosmetics floor area effectively becomes an open market, with multiple firms competing for customers in a shared space. This retailing system is a prevalent practice in China (Li et al. 2010) and is becoming more common in the United States (Jerath and Zhang 2010).[5] In our setting, the department store sets the counter locations and schedules the worker shifts. We observe cosmetic sales for 11 of the 15 counters over a four-year period (January 1, 2003–December 31, 2006).

[2] Ching (2010) assumes that a consumer can observe others' experience after their choices in an aggregate learning context, which roughly corresponds to the output in this study.

[3] There is a related literature on learning and knowledge transfer, but no studies dynamically model experience- and peer-based learning at the individual level. Azoulay et al. (2010) and Oettl (2012) observe contemporaneous knowledge-based peer effects among scientists. Others infer knowledge transfer by linking improved team performance with team tenure (Edmondson et al. 2001, Pisano et al. 2001, Huckman et al. 2009). Sociological work also infers knowledge transfer through worker network structure (Ingram and Roberts 2000, Reagans and McKevily 2003).

[4] See Mantrala et al. (2010) for a review of sales force modeling.

[5] In fact, the cosmetics sections at almost all of the major U.S. department stores (e.g., Bloomingdale's, Macy's, Neiman Marcus, Nordstrom, Saks Fifth Avenue) are populated using this system (Anderson 2006).

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Table 1 Brand-Level Summary Statistics

	Compensation system	Annual sales revenue (¥1,000)	Average price (¥) All products	Skin care	Makeup	Average transaction size (units)
Brand 1	IC	3,742.9	131.3	140.4	107.0	1.83
Brand 2	TC	3,602.3	106.6	119.7	93.9	1.54
Brand 3	TC	3,145.1	85.3	89.7	79.6	1.57
Brand 4	TC	1,196.1	127.8	141.8	92.0	1.71
Brand 5	TC	682.0	47.8	55.2	44.4	1.60
Brand 6	IC	1,058.3	130.0	143.7	103.7	1.56
Brand 7	IC	1,752.4	150.8	164.2	110.8	1.34
Brand 8	IC	525.5	108.4	115.1	73.3	1.71
Brand 9	IC	1,054.9	118.1	133.5	74.2	2.06
Brand 10	IC	763.9	136.2	143.8	100.4	1.66
Brand 11	IC	725.8	109.8	114.4	102.7	1.48

Note. US$1 = ¥8.1 on average during the sample period.

Descriptive statistics for these brands are summarized in Table 1. The counters vary both in average price and total revenue. The 11 brands in our data use two different compensation systems: team-based commission (TC) and individual-based commission (IC).[6]

Selling cosmetics is far more challenging than selling other categories such as groceries. Given the average item price of ¥114 (see Table 1), cosmetics are luxury products for most Chinese consumers, especially during the sample period. Customers have unique product needs; even for the same product (e.g., lipstick) there are many colors and scents that customers evaluate differently. A newly hired salesperson must learn the many product attributes and how they match customers with unique needs. She must also be patient but persuasive dealing with customers. Interviews with the store manager reveal that the selling process can last an entire hour before a customer makes a decision.

There are two major cosmetic categories: skin care and makeup. Skin care products are typically more expensive than makeup products (average prices of ¥124 and ¥89, respectively). Whereas customers can immediately verify the benefits of makeup in improving appearance, the value of skin care products are only observable through long-term use. Most Chinese customers seek "whitening" and "smoothing" benefits from skin care, which may not be obvious even after long-term use, making skin care products credence goods (Darby and Karni 1973). The information asymmetry of credence goods creates moral hazard (Emons 1997), making customers cautious in buying. Salespeople must be skillful to justify the products' high prices. Our interviews with cosmetics salespeople and managers in both China and the United States consistently revealed that selling skin care products is more challenging than selling makeup.

Table 2 describes the salespeople in the data. Ninety-two female salespeople worked for the 11 brands over our study period with 44% turnover. The "Entries" and "Exits" columns show that 53 new salespeople entered and 41 existing workers departed. All salespeople were nearly identical demographically: female, Han Chinese, and between 20 and 35 years old. Although this homogeneity reduces concerns about endogenous sorting on worker characteristics, it also precludes us from using observable demographics to estimate selection processes. We do not observe prior working experience. Table 2 also reports the average tenure length across counters truncated on both the left and right sides of the data.

When a salesperson completes a sale, the cashier records the salesperson's unique ID, the product identity, quantities, prices, and time of sale, providing detailed data about each sale. In each counter, salespeople typically work in one of three *overlapping* shifts during the seven days per week the store is open: the first shift from 9 A.M. to 3 P.M., the second shift from 12 P.M. to 6 P.M., and the third shift from 3 P.M. to 9 P.M. The manager schedules worker shifts at the beginning of each month so as to ensure each person will rotate days and times. Although many salespeople have preferences for shifts or days, they all evenly rotate each for fairness reasons. Salespeople may also have preferences for coworkers, but again, for fairness reasons the manager ensures that each salesperson has an equal chance of working with other within-counter peers. The manager also stated that shifts are assigned independently across counters. Although each salesperson's time at each shift and with specific peers is roughly the same in the long run (e.g., a month), within a shorter window (e.g., a week), we

[6] The commissions of TC counters are based on the monthly total counter sales revenue, whereas for IC counters they are based on personal monthly sales.

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Table 2 Cosmetics Team Descriptive Statistics

	Salespeople in sample period	Mean days worked	Entries	Exits	New salesperson pairing w/high-ability peers (%)	New salesperson pairing w/low-ability peers (%)
Brand 1	13	749.22	8	5	51.10	48.90
Brand 2	14	373.31	9	7	50.60	49.40
Brand 3	7	1,084.89	3	3	49.70	50.30
Brand 4	6	1,169.31	3	2	49.60	50.40
Brand 5	9	697.78	6	4	50.10	49.90
Brand 6	5	802.59	2	2	48.80	51.20
Brand 7	9	602.19	5	4	52.50	47.50
Brand 8	5	561.52	2	2	51.40	48.60
Brand 9	11	361.19	8	6	47.60	52.40
Brand 10	5	1,087.49	2	2	49.10	50.90
Brand 11	8	541.17	5	4	51.70	48.30
All brands	8.36	730.06	4.82	3.73	49.80	51.20

observe large fluctuations in the data. These short-term fluctuations create exogenous shocks that are important in identifying peer learning.

In addition, we identify two other sources of variation in peers within and across counters that are plausibly exogenous. First, the law requires workers on average to have two days off per week. The store is open seven days per week, and weekends and public holidays such as New Year's are its busiest time. It cannot let salespeople off during these days, nor do salespeople want to be, given their commission-based pay. Salespeople typically work for long periods without days off, using accumulated vacation for longer breaks. A salesperson, on average, works 181 hours per month with a standard deviation of 61 hours. Across the sample period, we observe 562 times a salesperson is absent for more than two days. The average absence is 4.5 days, with a standard deviation of 5.6, and the maximum is 63 days. Leaves are typically applied for well in advance and are almost always granted by managers. This serves as an instrument for identifying peer-based learning. A new salesperson who frequently works alone because more experienced peers are on vacation may have a completely different learning process compared with one who spends her first weeks observing and learning from peers.

Second, from the beginning of our sample (January 1, 2003) until the end of October 2004, the cosmetics department occupied the store's east gate area, which was the main customer entry. The floor plan, location, and compensation system of the counters in this period is presented in the left panel of Figure 1. On November 1, 2004, all cosmetics counters relocated to the west gate area as a result of construction outside the store forcing relocation of the main entrance. The right panel of Figure 1 presents the floor plan and location of the cosmetics counters after relocation. Such a relocation offers another exogenous variation in the pool of cross-counter competing peers—each salesperson after relocation faces a new set of peers from competing counters.

2.1. Productivity Growth of New Salespeople

Figure 2 plots the productivity growth of new salespeople in their first 25 weeks of service (relative to

Figure 1 Cosmetics Floor Layout Before and After Relocation

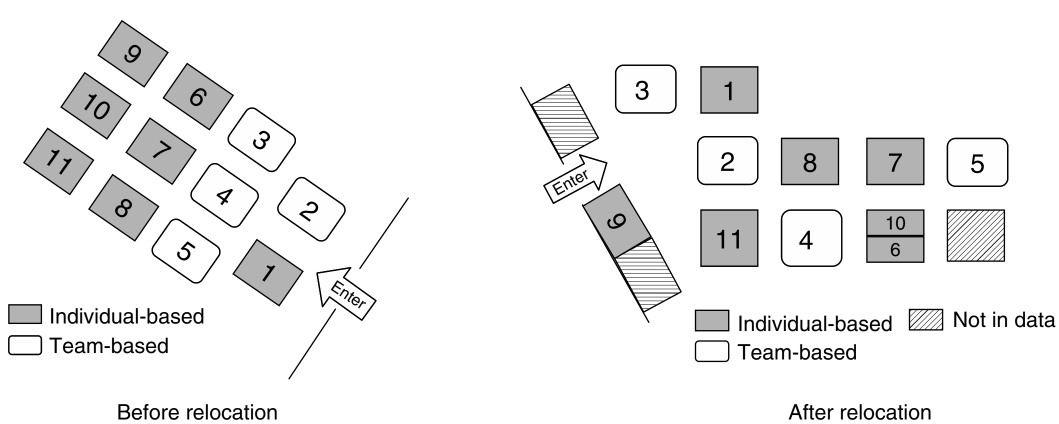

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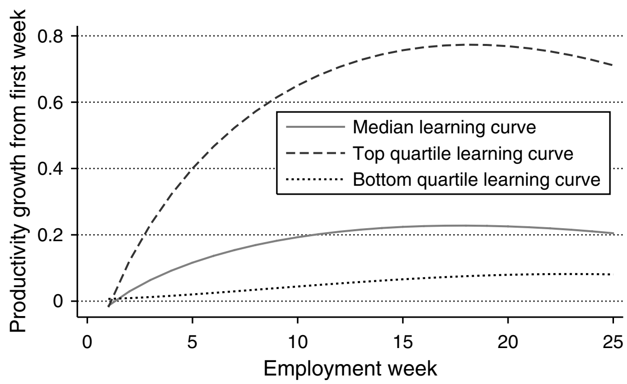
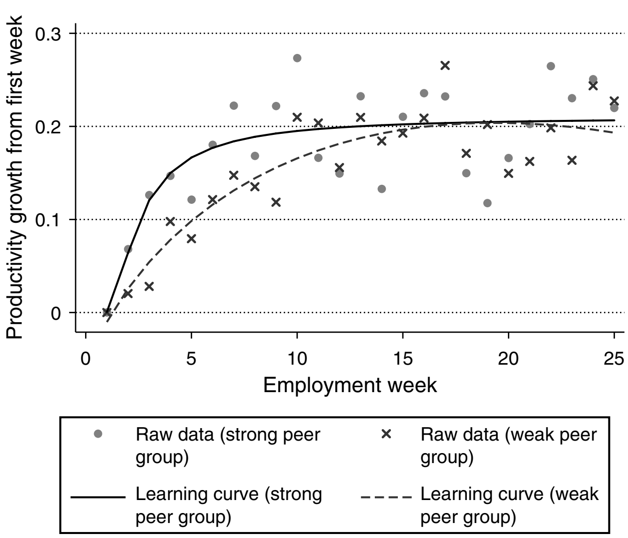
Figure 2 **Heterogeneity in the Productivity Growth of New Salespeople**



the average hourly sales in the first week). The middle curve is the nonparametric smoothed "learning curve" averaged over all new salespeople, showing that learning occurs mainly in the first three months. There is a large variation across salespeople. The curves show that the lower and upper quartiles of productivity change for all salespeople are very different. This variation is partly driven by heterogeneity in learning ability across salespeople; however, it is also partly driven by the difference in the learning process as a result of the variation in the pool of peers in different weeks.

Figure 3 presents basic evidence that this variation in learning rates is influenced by exposure to peers. The solid dots represent the productivity growth (relative to the first week) of all new salespeople assigned more hours in the first two weeks with a "strong peer group."[7] The x marks represent those assigned more hours in the first two weeks with a "weak peer group." There are large weekly productivity fluctuations as a result of seasonal and other factors for which we do not control; however, the productivity growth of the former group consistently exceeds the latter in the first 10 weeks. The solid line, reflecting the smoothed learning curve of the "strong" peer group, and the dashed line, reflecting the smoothed learning curve of the "weak" peer group, confirm this observation. The difference diminishes over time, likely because of the random worker assignment averaging out the learning of the two groups in later weeks. Regardless, the impact of heterogeneous peer mix in the first two weeks is considerable and suggests that peers indeed impact new salespeople' productivity in future weeks.

Figure 3 **Impact of Peer Ability in the First Two Weeks on Productivity Growth**



Note. The strong peer group represents new workers assigned to the above average peer group in the first two weeks of employment.

3. Production Function and Salesperson Learning

In this study, the selling ability of a salesperson may evolve over time through learning, thereby impacting her future sales. Suppose that there are I salespeople working for J counters in the store in week t and that each salesperson deals with N potential customers. Salesperson i's sales revenue when selling to the nth customer, Y_{it}^n, is a function of her own selling ability, $\hat{Y}_{it}$, and other external factors, $\mathbf{Z}_{jt}$. Brand fixed effects are included in $\mathbf{Z}_{jt}$ to capture differences in product quality and compensation for salespeople's effort. We specify the production function as follows:[8]

$$Y_{it}^n = \hat{Y}_{it} \cdot e^{\mathbf{Z}_{jt}\boldsymbol{\beta}} \cdot \tilde{\eta}_{it}^n, \tag{1}$$

where $\tilde{\eta}_{it}^n$ is an error term representing demand shocks such as storewide promotions, competition among salespeople, and the customer's preferences.

Defining $\tilde{\eta}_{it} = \sum_{n=1}^N \tilde{\eta}_{it}^n$, salesperson i's weekly sales can be aggregated from Equation (1) as follows:

$$Y_{it} = \hat{Y}_{it} \cdot e^{\mathbf{Z}_{jt}\boldsymbol{\beta}} \cdot \tilde{\eta}_{it}. \tag{2}$$

Let $y_{it} = \ln(Y_{it})$, $\hat{y}_{it} = \ln(\hat{Y}_{it})$, and $\eta_{it} = \ln(\tilde{\eta}_{it})$; we then obtain the following weekly sales function of salesperson i:

$$y_{it} = \hat{y}_{it} + \mathbf{Z}_{jt}\boldsymbol{\beta} + \eta_{it}. \tag{3}$$

[7] This is defined as the salespeople whose revenue over the study period is above the median level within the same counter. Likewise, the "weaker peer group" consists of those salespeople whose sales revenue is below the median.

[8] We assume that Y_{it}^n is continuous and left-truncated at zero (i.e., no transaction). This specification allows that a high-ability salesperson not only can sell more effectively but also can cross-sell other products or convince customers to buy more expensive items. For illustration purposes, this production function abstracts away from the heterogeneity of consumer needs and preferences. In reality, different production functions may be involved when dealing with different customer types; the selling task thus will be even more complicated.

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This production function demonstrates the positive relationship between a salesperson's selling ability and her (logged) weekly sales. In the empirical analysis in the next section, we will focus on the change in this weekly sales for each salesperson.

Assume that a general selling process involves K activities, $a^1, \ldots, a^K$, each representing a task that may increase the chance of a successful transaction (e.g., warmly greeting customers, comparing product attributes). To maximize sales under time and effort constraints, any salesperson i must choose the optimal set of activities. Correspondingly, we specify the selling ability $\hat{Y}_{it}$ as a general function $\hat{Y}_{it} = y(a_{it}^1, \ldots, a_{it}^K; \psi)$. The complexity of the job task is captured by the dimension of parameters ψ, which will increase as more activities are involved or the function $y(\cdot)$ becomes more complicated (e.g., many local optima and kinks when mapped to activities). A salesperson's knowledge of sales techniques is defined as how much she knows about ψ. Let her prior belief of the true values of ψ be represented by a (continuous or discrete) distribution $F(\psi)$ with mean ψ^0. The difference between ψ and ψ^0 indicates the bias in belief, and the dispersion of F represents the uncertainty of belief. Conditional on the compensation system (e.g., IC or TC) and work ethic (e.g., cost of effort), salespeople may invest different amounts of time and effort to their job; still, with a better knowledge (i.e., less bias and uncertainty in belief), a salesperson is able to choose a better combination of activities $a_{it}^1, \ldots, a_{it}^K$ and thus achieve higher sales. The salesperson's knowledge of sales techniques thus has a direct correspondence with $\hat{Y}_{it}$, which will in turn positively correlate with sales Y_{it} (see Equations (2) and (3)).

To learn ψ, the salesperson may experiment with different activities and update her priors based on sales outcomes. This is the learning-by-doing mechanism where time and experience allows her to experiment and hence gain better knowledge. The short-run cost of learning-by-doing, however, is that experimentation may yield lost customers and commissions, making her unwilling to experiment. The learning process can be particularly slow for complicated job tasks with high-dimensional ψ, because the salesperson must experiment repeatedly to learn the true values.

Alternatively, the salesperson may observe the activities and sales outcomes from within- and cross-counter peers[9] and use these to update $F(\psi)$. Peers with different abilities may choose different activities. If the average success rate of sales interactions among peers is low, observing high-ability peers will enable the salesperson to learn faster and achieve higher future sales. There is no risk of losing customers, but the salesperson has to exert effort to closely observe peer activities. Another peer-based learning mechanism is that peers teach the salesperson how different activities can lead to different outcomes. Thus, the knowledge of ψ is directly passed. The higher the ability a peer has, the less noise there is in the knowledge that she teaches. Such peer-based learning through teaching, however, requires effort and time from both parties. Peers must therefore have an incentive to teach, making teaching unlikely for salespeople in a competitive relationship either within or across counters.[10]

4. Identification and Simple Regression Results

Identifying peer-based learning is challenging because, similar to any analyses on social interactions (e.g., Bell and Song 2007, Tucker 2008, Godes and Mayzlin 2009, Hartmann 2009, Nair et al. 2010), factors other than causal effects of agents' actions on each other could create spurious correlations in behavior (Manski 1993, Hartmann et al. 2008). This is particularly a concern given that we cannot directly observe learning among the salespeople. In this section we discuss our identification strategy and the assumptions critical to our empirical investigation.

4.1. The Identification of Learning

The learning mechanism we discussed in the previous section implies relationships between a salesperson's own work experience or peer interactions and her selling ability, which has a monotonic relationship with sales. Since we cannot directly observe learning, our empirical strategy is to first use sales data to identify how salesperson ability changes with own work experience and peer interactions. After that, we examine whether the results are consistent with the learning mechanism and also rule out alternative explanations for the results that are not based on peer learning.

In our empirical investigation, salesperson ability is inferred from sales in each week. Equation (1) shows a monotonically positive relationship between sales Y_{it} and ability $\hat{Y}_{it}$ in week t. Two key assumptions are required to identify our empirical model. First,

[9] We assume that peers cannot fully hide their techniques. Even if they can, hiding is likely costly (e.g., annoying customers if she keeps a low voice to avoid being overheard). Furthermore, the focal salesperson can learn from other within- and cross-counter peers, so hiding does not have significant benefit for a single peer (unless everyone colludes to do so).

[10] We do not explicitly model competition in this paper. See Chan et al. (2014) for extensive discussion of contemporaneous competition among salespeople. As we argue in the next section, however, our estimates of the learning effects are still consistent given the worker shift assignment.

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we assume that salesperson ability is impacted by own work experience and peer interactions from previous weeks but not from the current week.[11] Second, we assume that, because of the quasi-random worker assignment, changes in the pool of peers and shifts in each week are exogenous to worker ability and demand shocks. Extensive tests of the randomness of worker assignment, presented in Appendix A, demonstrate that both new and experienced salespeople are equally likely to work in any given shift and with any given peer.

Given the assumption that the shifts and pool of peers in each week are randomly assigned, the error term $\tilde{\eta}_{it}^{n}$ is exogenous in Equation (1); therefore, controlling for $\mathbf{Z}_{jt}$, $\hat{Y}_{it}$ can be identified from the average hourly sales in the week.[12] Then, based on the first assumption, the correlations between the change of abilities, $\hat{Y}_{it} - \hat{Y}_{i,t-1}$, and the salesperson's own work experience and peer interactions in the previous week can be used to infer the learning effect since our framework has monotonic relationships between learning and salesperson knowledge and ability. The correct inference, however, requires us to address several identification concerns. First, if salespeople with high learning ability are more likely to work more hours, the correlation between $\hat{Y}_{it} - \hat{Y}_{i,t-1}$ and work experience will be an upward-biased estimate of the true relationship. This is not an issue, however, because our random shift assignment ensures that work hours across salespeople are not significantly different, except for long leaves that are exogenous to salesperson learning ability.

The reflection problem, stating that two workers might simultaneously impact each other's productivity (Manski 1993), is a major issue in identifying the effect of peer interactions on worker ability because estimates might reflect both directions of peer effects. Our study, however, investigates how a worker's productivity is influenced by peer ability that is lagged one week. As Manski (1993) acknowledges, this type of dynamic model does not suffer the same reflection problem as contemporaneous models so long as the time lag is appropriately determined. We also note that Figure 2 shows the productivity of new salespeople to be time varying; that is, our data are not at the stable temporal equilibrium, a necessary condition for identifying peer effects in dynamic models (Manski 1993, p. 540). Furthermore, because the peer interaction precedes the productivity change, correlations are not due to contemporary peers at the same or nearby counters.

Another identification concern is mean reversion—a salesperson may experience lower sales when working with star peers in the current week, with sales recovering the next week when she works with other, lower-ability salespeople. In such an explanation, what appears to be productivity growth is really mean reversion from a negative contemporaneous peer effect in the prior period. A simple peer effects model helps to illustrate why this potential identification problem is unlikely to fully explain peer ability impacting long-term productivity growth in our setting given our pseudo-random worker assignment. Suppose a salesperson's sales at week t, y_t, are driven by the number of hours she works together with all kinds of peers in the current week, h_t, as $y_t = \alpha_0 + \alpha_1 h_t + \varepsilon_t$, where ε_t is an error term, and α_1 represents the true contemporary peer effect. The number of work hours is used as a proxy for the level of interaction between the salesperson and her peers. Suppose researchers were to instead misspecify a peer-based learning model as $y_t = \theta_0 + \theta_1 \tilde{h}_{t-1} + \mu_t$, where $\tilde{h}_{t-1}$ is the number of hours the salesperson works with all types of peers in the previous week, and μ_t is an error term that in this case will consist of the influence from h_t. If h_t correlated with $\tilde{h}_{t-1}$, researchers would wrongly infer peer-based learning from a significant estimate of θ_1. However, Tests 3–6 in Table A.2 in Appendix A show that the average number of hours a salesperson works with high- or low-ability peers in the current week is independent of the number of hours working with high- or low-ability peers in the previous week, within and across counters. In this case, h_t and $\tilde{h}_{t-1}$ are uncorrelated, and consequently, μ_t is independent from $\tilde{h}_{t-1}$. If the first model were true, the estimate of θ_1 when estimating the second model should be insignificant.[13]

4.2. Addressing Endogenous Hiring in a Simple Regression Model

Finally, we are concerned that salespeople are endogenously selected based on attributes unobservable to the researcher that will influence productivity growth after being hired. This potential problem can be illustrated using a simple model. Assume that in each week t the ability of a salesperson i, $\hat{y}_{it}$, is dynamically accumulated as follows:

$$\hat{y}_{it} = \hat{y}_{i,t-1} + \lambda_i + \mathbf{h}_{i,t-1}\boldsymbol{\theta}, \tag{4}$$

[11] Consequently, we should treat the effect of peer-based learning and learning-by-doing on sales in our empirical model as the carryover effect from the previous week. Learning in the current week cannot be separated from the competitive or cooperative relationship with peers who are working together in the same week.

[12] Otherwise, we cannot distinguish from data whether higher sales are due to higher selling ability, assigning shifts with high demand, or working together with lower-ability competitive peers.

[13] Alternatively, we may include both h_t and $\tilde{h}_{t-1}$ in the regression. As long as they are not perfectly correlated, θ_1 and α_1 can be separately recovered.

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where $\mathbf{h}_{i,t-1}$ is a vector of the logged hours the salesperson works with high- and low-ability peers (as a proxy for the level of interaction), within and across counters, in the previous week. In this specification, salesperson i's ability adjusts every week by a constant λ_i representing the unobserved attributes affecting her productivity growth, which is independent from the peer assignment. The effect of peer interactions are captured by $\boldsymbol{\theta}$. Assume the salesperson works for T weeks. Iterating backward until the salesperson's first week, we obtain $\hat{y}_{it} = \hat{y}_{i,0} + \lambda_i \cdot T + (\sum_{s=1}^{T-1} \mathbf{h}_{is})\boldsymbol{\theta}$, where $\hat{y}_{i,0}$ is a parameter of the unobserved attributes that determines salesperson i's selling ability before employment.

Worker selection could bias the estimate of $\boldsymbol{\theta}$ in two ways. First, if a firm selects salespeople with higher $\hat{y}_{i,0}$, the regression will wrongly infer the firm's new salespeople have faster productivity growth and, since they work with other high-ability salespeople at the same counter, obtain an upward-biased estimate of $\boldsymbol{\theta}$ for working with high-ability peers. Second, if a firm is able to select salespeople with higher λ_i, new salespeople are also more likely to have peers with high ability. By similar reasoning, the regression may obtain an upward-biased estimate of $\boldsymbol{\theta}$ for working with high-ability peers.

To examine whether the potential salesperson ability change in our data is indeed driven by peer interactions instead of worker selection and hiring, we run a first-difference regression using $y_{it} - y_{i,t-1}$ (the log of the new salesperson's sales growth in the first 12 weeks of employment) as the dependent variable.[14] From Equations (3) and (4), we obtain

$$y_{it} - y_{i,t-1} = \lambda_i + \mathbf{h}_{i,t-1}\boldsymbol{\theta} + (\mathbf{Z}_{it} - \mathbf{Z}_{i,t-1})\boldsymbol{\beta} + (\eta_{it} - \eta_{i,t-1}). \quad (5)$$

In the equation, we have differenced out and hence controlled for heterogeneity in initial salesperson ability. The remaining selection issue is heterogeneity in λ_i, which we address in two ways. First, we directly estimate λ_i using our panel data. By doing so, our setup is equivalent to a difference-in-differences regression. Second, we also use firm fixed effects to control for selection. Since the ability of firms to attract salespeople with different learning potential should be relatively time invariant, the worker selection issue will be mitigated by estimating these fixed effects.

Among the 53 newly hired salespeople in the data, six quit within the first three months. Their average hourly sales were far below those who stayed longer. We are concerned that these early exits may create another selection issue. To examine how the early quitters impact our results, we use two sets of data in our regression: the whole sample and one using only salespeople whose tenure was longer than three months. Finally, we also interact $\mathbf{h}_{i,t-1}$ in Equation (5) with the indicators of the second and third months of employment to account for the fact that the effect of peer interactions may not be stable over time as a salesperson's ability grows.

Regression results are presented in Table 3 with robust standard errors clustered by salesperson. The main effect of peer interactions on sales (ln(*Hours with high-ability peers last week*) and ln(*Hours with low-ability peers last week*) for both within-counter and cross-counter cases) is consistent in sign and magnitude across the four specifications, suggesting that including salesperson or counter fixed effects and using different samples do not substantially impact our results. In a new salesperson's first month, a 1% increase in hours working with high-ability peers at the same counter in the previous week leads to about 0.4% gains in productivity in the current week. The model preserves the gain in future weeks. This effect declines with tenure, although the decline is only significant in the third month in the first and second specifications, implying that the salesperson is impacted less by peers as she gains ability. Working with low-ability peers at the same counter in the first month has a negative effect on productivity growth that is marginally significant in the third and fourth specifications, but the magnitude is far smaller than the positive effect from working with high-ability peers.

Table 3 also illustrates the long-term benefit of working with high-ability peers at adjacent counters—in the first month of employment, a 1% increase in hours with high-ability salespeople at competing counters in the previous week leads to 0.15% to 0.24% productivity gains in the current and future weeks. This effect, although declining across subsequent months, is still quite substantial in the second and third months. Working with low-ability salespeople at other counters, however, does not impact productivity growth. In summary, these results provide clear initial evidence of the positive and permanent impact to new salespeople of working longer in the previous week with high-ability peers at the same and adjacent counters, which is consistent with the learning mechanism, but different from the contemporary peer effects in the literature (Mas and Moretti 2009, Chan et al. 2014). The results are not due to the endogenous worker hiring because the model controls for worker heterogeneity.

[14] We restrict our analysis to the first 12 weeks based on conversations with the store manager, who suggested that a new worker would take about three months to obtain a full knowledge of products and sales techniques.

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Table 3 Reduced-Form Evidence of Peer-Based Learning

Sample	(1) All hires	(2) Stay > 3 months	(3) All hires	(4) Stay > 3 months
	Dependent variable: *Sales from last week*			
Within-counter				
ln(*Hours with high-ability peers last week*)	0.399**	0.389**	0.369**	0.364**
	(0.071)	(0.083)	(0.086)	(0.122)
ln(*Hours with high-ability peers last week*) × *Month 2*	−0.080	−0.086	−0.035	−0.049
	(0.107)	(0.110)	(0.103)	(0.141)
ln(*Hours with high-ability peers last week*) × *Month 3*	−0.230**	−0.257**	−0.156	−0.229
	(0.109)	(0.121)	(0.121)	(0.169)
ln(*Hours with low-ability peers last week*)	−0.056	−0.083	−0.126*	−0.180*
	(0.063)	(0.070)	(0.070)	(0.092)
ln(*Hours with low-ability peers last week*) × *Month 2*	−0.101	−0.013	−0.098	0.071
	(0.089)	(0.091)	(0.090)	(0.096)
ln(*Hours with low-ability peers last week*) × *Month 3*	−0.028	−0.081	−0.002	−0.046
	(0.086)	(0.095)	(0.107)	(0.099)
Cross-counter				
ln(*Hours with high-ability peers last week*)	0.236**	0.188**	0.178**	0.150*
	(0.065)	(0.073)	(0.061)	(0.083)
ln(*Hours with high-ability peers last week*) × *Month 2*	−0.173**	−0.040	−0.117*	−0.003
	(0.082)	(0.092)	(0.068)	(0.099)
ln(*Hours with high-ability peers last week*) × *Month 3*	−0.023	−0.069	−0.006	0.024
	(0.087)	(0.095)	(0.075)	(0.127)
ln(*Hours with low-ability peers last week*)	−0.002	−0.025	−0.011	−0.011
	(0.052)	(0.057)	(0.046)	(0.072)
ln(*Hours with low-ability peers last week*) × *Month 2*	0.031	0.101	−0.050	−0.039
	(0.075)	(0.080)	(0.073)	(0.121)
ln(*Hours with low-ability peers last week*) × *Month 3*	0.035	0.032	−0.062	−0.184*
	(0.084)	(0.085)	(0.079)	(0.094)
R^2	0.252	0.247	0.129	0.122
Number of observations	550	517	550	517
Month and year dummies	Yes	Yes	Yes	Yes
Counter fixed effects	No	No	Yes	Yes
Worker fixed effects	Yes	Yes	No	No

Note. Robust standard errors are clustered at the worker level.
$^{*}p < 0.10$; $^{**}p < 0.05$.

5. A Comprehensive Learning Model

Figure 3 and Table 3 present initial evidence of the effect of peer interactions on the learning of newly hired salespeople. Based on the learning mechanisms we have examined, we now build a more comprehensive model that incorporates the relative impact of peer-based learning, learning-by-doing, and forgetting on new salesperson productivity growth. We specify peer-based learning as a function of not only the number of work hours but also the difference in ability between the salesperson and her peers. Therefore, the magnitude of learning will change over time as the salesperson's ability grows, offering a rationale for our findings in Table 3 that the effect of working with high-ability peers decreases over time. In our model, we further extend these specifications to examine the learning of incumbent salespeople as well.

5.1. Modeling Peer-Based Learning, Learning-by-Doing, and Forgetting

In our analysis, a salesperson's peers are defined as all other cosmetics salespeople who either work at the same counter (*within-counter* peers or *inside* peers) or work in any adjacent counter (*cross-counter* peers or *outside* peers).[15] We use a reduced-form approximation to model how the (logged) ability $\hat{y}_{it}$ in Equation (3) changes over time through peer interactions, which reflects peer-based learning.

Let N_{jh} and $N_{j'h}$ denote the sets of peers that the salesperson i works with within her own counter j

[15] Salespeople at distant counters cannot be directly observed or interacted with during work time; therefore their techniques are difficult to learn. Chan et al. (2014) show from the same data source that cross-counter peer effects rapidly diminish with distance between counters.

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and in any adjacent counters j' in any hour h, respectively. Also let $card(N_{jh})$ and $card(N_{j'h})$ be the numbers of elements in N_{jh} and $N_{j'h}$, respectively. We assume that $\hat{y}_{it}$ in week t is affected by peer interactions in the previous week $t-1$. Since salespeople work with different peers in different hours throughout the week, we first specify the peer interaction at the *hour* level. We assume that $\hat{y}_{it}$ is affected by the difference between her ability and the ability of peers. We further assume that $\hat{y}_{it}$ is affected by the average of those ability differences in any hour h the salesperson works.[16] We then aggregate these hourly interactions to the *week* level and normalize by the total work hours of i in week t, $H_{i,t-1}$. Suppose the effect is positive. By working fewer hours in a week, a newly hired salesperson's ability growth suffers as she learns less from peers, affecting her sales not only in the next week but also in weeks after. Also, as the salesperson's ability improves, learning from peers will diminish. Given that i's ability will similarly affect the learning of her peers k, her ability change will in turn influence k's productivity change in the week after. As a result, the productivity changes of all salespeople, within and across counters, will be dynamically correlated with one another.

Previous studies have typically modeled learning-by-doing by using past production as a proxy for past experience (e.g., Benkard 2000). However, if we used past sales, a high-ability salesperson would always have higher work experience than her peers, even though they had worked the same number of hours. Yet a salesperson may improve her skills through repeated customer interaction and activity experimentation even though this does not always generate sales; therefore, we assume that a salesperson's ability growth is affected by (the log of) the total number of hours she worked in the previous week, $h_{i,t-1}$. Finally, we model forgetting as the fraction of ability lost from the previous week if the salesperson did not work. Based on the above discussion, we specify $\hat{y}_{it}$ as follows:

$$\hat{y}_{it} = \gamma\hat{y}_{i,t-1} + \theta_1 \sum_h \left\{ \frac{\sum_{k\in N_{jh}} (\hat{y}_{k,t-1} - \hat{y}_{i,t-1})}{card(N_{jh})} \cdot \frac{1}{H_{i,t-1}} \right\} + \theta_2 \sum_h \left\{ \frac{\sum_{k'\in N_{j'h}} (\hat{y}_{k',t-1} - \hat{y}_{i,t-1})}{card(N_{j'h})} \cdot \frac{1}{H_{i,t-1}} \right\} + \lambda h_{i,t-1} + \tau_{it}. \quad (6)$$

In this dynamic setup, $\hat{y}_{i,t-1}$ in the previous week carries over to $\hat{y}_{it}$ in the current week, implying that level of knowledge or ability has a long-term impact on future sales. The parameter γ, which captures knowledge carryover, implies forgetting or depreciation in ability with any estimate less than 1. Parameters θ_1 and θ_2 represent within-counter and cross-counter peer-based learning, respectively. The parameter λ captures learning-by-doing from work experience. Finally, τ_{it} is an error term representing "learning shocks" that are not captured in our model (e.g., the salesperson may enroll in a training course). The major difference between the learning shocks and demand shocks on sales is that the former will be carried over to future periods (as capital of knowledge), and the latter will not. This model is different from previous studies on contemporary peer effects since the current effect from peers on $\hat{y}_{it}$ will impact $\hat{y}_{is}$ in any future week s.

Suppose that there are I salespeople. We then have I simultaneous Equations (6), each for one salesperson. Let $\hat{\mathbf{y}}_t = (\hat{y}_{1t}, \hat{y}_{2t}, \dots, \hat{y}_{It})'$ be the vector of their ability in week t, and let $\mathbf{h}_{t-1} = (h_{1,t-1}, h_{2,t-1}, \dots, h_{I,t-1})'$ be the vector of their (logged) work hours in the previous week. The equation system can be transformed into a matrix format as follows:

$$\hat{\mathbf{y}}_t = \mathbf{\Theta}_{t-1}\hat{\mathbf{y}}_{t-1} + \lambda\mathbf{h}_{t-1} + \boldsymbol{\tau}_t, \quad (7)$$

where $\boldsymbol{\tau}_t = (\tau_{1t}, \tau_{2t}, \dots, \tau_{It})'$, and $\mathbf{\Theta}_{t-1}$ is an I by I square matrix with the $[i,s]$ element (assume salesperson i works in counter j) as

$$\mathbf{\Theta}_{t-1}[i,s] = \begin{cases} \gamma - (\theta_1 + \theta_2), & \text{if } s = i, \\ \theta_1 \sum_h \dfrac{1\{s \in N_{jh}\}}{card(N_{jh})} \cdot \dfrac{1}{H_{i,t-1}}, & \text{if } s \neq i \text{ and both work at the same counter,} \\ \theta_2 \sum_h \dfrac{1\{s \in N_{j'h}\}}{card(N_{j'h})} \cdot \dfrac{1}{H_{i,t-1}}, & \text{if } s \neq i \text{ and both work at different counters,} \end{cases} \quad (8)$$

where $1\{s \in N_{jh}\}$ and $1\{s \in N_{j'h}\}$ are indicators that peer s works during hour h in week $t-1$.

Let $\mathbf{y}_t = (y_{1t}, y_{2t}, \dots, y_{It})'$ be the vector of the (logged) average hourly sales revenues of the I salespeople in week t. Also, let $\mathbf{Z}_t$ be a matrix with the row vectors $\mathbf{Z}_{jt}$ for all salespeople.[17] From Equation (3), we can establish a relationship between salespeople' sales in week t and own and peers' ability in week $t-1$ as

$$\mathbf{y}_t = \mathbf{\Theta}_{t-1}\hat{\mathbf{y}}_{t-1} + \lambda\mathbf{h}_{t-1} + \mathbf{Z}_t\boldsymbol{\beta} + \boldsymbol{\tau}_t + \boldsymbol{\eta}_t. \quad (9)$$

[16] Since $\hat{y}_{it}$ is the log of $\hat{Y}_{it}$, the differences measure the log of the ratio of abilities of two salespeople.

[17] In our regressions, these include year (Years 2–4), month (February–December), day of week (Monday–Saturday), and brand indicators. With brand fixed effects, $\hat{y}_{it}$ represents the difference between the salesperson's ability and the average ability of all salespeople at the same counter.

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We can backward iterate the above expression $t-1$ times to obtain

$$\mathbf{y}_t = \left(\prod_{g=1}^{t-1} \mathbf{\Theta}_{t-g}\right)\hat{\mathbf{y}}_1 + \lambda \sum_{g=1}^{t-1}\left[\left(\prod_{h=1}^{g-1} \mathbf{\Theta}_{t-h}\right)\mathbf{h}_{t-g}\right] + \mathbf{Z}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t, \tag{10}$$

where $\hat{\mathbf{y}}_1$ represents the *initial* ability of all salespeople, and $\mathbf{h}_{t-g} = (h_{1,t-g}, \ldots, h_{I,t-g})'$. We estimate $\hat{\mathbf{y}}_1$ as fixed effects parameters. Controlling for the individual fixed effects is important to address the selection issue of worker hiring. The error term $\boldsymbol{\varepsilon}_t$ is a combination of demand shocks and past learning shocks as follows:

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\tau}_t + \sum_{g=1}^{t-1}\left[\left(\prod_{h=1}^{g} \mathbf{\Theta}_{t-h}\right)\cdot \boldsymbol{\tau}_{t-g}\right] + \boldsymbol{\eta}_t. \tag{11}$$

Because of learning, $\boldsymbol{\varepsilon}_t$ is serially correlated for each salesperson through $\boldsymbol{\tau}$'s across periods. This implies that we have to allow for a general structure of heteroskedasticity for $\boldsymbol{\varepsilon}_t$ in our estimation.

5.2. Model Estimation

A challenge of estimating the model is that it is dynamic and nonlinear. The $\mathbf{\Theta}$'s of different weeks are functions of unknown parameters γ, θ_1, and θ_2 (see Equation (8)). In Equation (10), they multiply themselves over weeks and interact with the vector of salesperson fixed effects $\hat{\mathbf{y}}_1$.[18] If we simultaneously estimate Equation (10) for all parameters via a nonlinear estimation approach, the dimensionality problem is severe (the number of parameters is 126 in the simplest model). Any numerical algorithm of searching for parameters will be very slow to converge and is likely to have the local optimum problem. To solve this problem, we modify the nested optimization procedure proposed by Chan et al. (2014). Our procedure recognizes that conditional on the three parameters γ, θ_1, and θ_2, $\mathbf{\Theta}$'s can be treated as covariates, and hence Equation (10) becomes linear in $\hat{\mathbf{y}}_1$. The nested procedure therefore starts by choosing some initial values for γ, θ_1, and θ_2, computing $\mathbf{\Theta}$'s from Equation (8) and then estimating $\hat{\mathbf{y}}_1$ (and other parameters including λ and $\boldsymbol{\beta}$) via standard linear least-square methods (inner procedure).

The outer procedure is to search for the optimal γ, θ_1, and θ_2, using standard numerical minimization routines that minimize the sum of squared errors as the criterion function value. Therefore, this nested optimization procedure is a nonlinear least-square (NLS) estimator. In our implementation, we use the Nelder and Mead (1965) simplex method. Since, given $\mathbf{\Theta}$'s, $\hat{\mathbf{y}}_1$ can be computed analytically using the linear method, this nested procedure is much faster than searching for all parameters in the model simultaneously. Furthermore, given $\mathbf{\Theta}$'s, the estimate $\hat{\mathbf{y}}_1$ is a unique optimum in minimizing the criterion function value. Local optima are not an issue in our model estimation—no matter what initial values for γ, θ_1, and θ_2 we use, the procedure always converges to the same values.

As we noted, $\boldsymbol{\varepsilon}_t$ is a function of $\mathbf{\Theta}_{t-h}$, implying a model with heteroskedasticity of errors. In particular, the longer a salesperson works in our data period, the larger the magnitude of $\text{var}(\boldsymbol{\varepsilon}_t)$ because of the unobserved learning accumulated from past periods. Subsequently, we compute the robust standard errors clustered at the individual salesperson level for the NLS estimator.

5.3. Extending the Model to Asymmetric Learning

Our model thus far is "symmetric" in the sense that the θ's do not differentiate between working with high- and low-ability peers. This may not be consistent with the learning mechanism in the previous section. To relax this restriction, we construct an asymmetric model of peer-based learning. The one difference between this new model and the symmetric model is that for the peer-based learning effects θ_1 and θ_2, we now estimate two separate effects, θ_g^a and θ_g^b, $g = 1, 2$. The former represents the within- or cross-counter peer-based learning effects from peers with higher ability (superiors), while the latter represents learning from those with lower ability (inferiors). Thus, for a focal salesperson i and her peer k, we estimate θ_g^a if $\hat{y}_{it} \le \hat{y}_{kt}$ and θ_g^b otherwise.

Though the extension is straightforward, the nested nonlinear estimation algorithm used to estimate our symmetric models cannot be directly applied to this model because, with asymmetric effects, $\hat{y}_{it}$'s now interact with indicator functions $\{\hat{y}_{it} \le \hat{y}_{kt}\}$ or $\{\hat{y}_{it} > \hat{y}_{kt}\}$. To solve this problem, we exploit that the indicators $\{\hat{y}_{it} \le \hat{y}_{kt}\}$ or $\{\hat{y}_{it} > \hat{y}_{kt}\}$ only depend on the ability ranking for salespeople j and k in week t. We use the average hourly sales for all salespeople in week t, $\bar{\mathbf{y}}_t$, to construct proxies $\{\bar{y}_{it} \le \bar{y}_{kt}\}$ or $\{\bar{y}_{it} > \bar{y}_{kt}\}$ for indicators $\{\hat{y}_{it} \le \hat{y}_{kt}\}$ or $\{\hat{y}_{it} > \hat{y}_{kt}\}$. These two rankings should be consistent with each other if the ability difference is the main driver of sales difference. Conditional on the ranking, we repeat the nested nonlinear algorithm as discussed before to estimate the four θ's and other parameters. After that, we reestimate all model parameters simultaneously via the nonlinear numerical algorithm, using the estimates we already obtained as the starting values. We find that the algorithm of this second step always immediately converges to the same starting values, indicating that the ability ranking based on

[18] The average tenure of workers in our sample is 104 weeks, making biased estimates from incidental parameter problems very unlikely (Chamberlain 1984). See Table 2 for counter-level tenure averages.

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the actual sales revenues is reliable. We also compare the actual sales revenue rankings $\{\bar{y}_{it} \le \bar{y}_{kt}\}$ and $\{\bar{y}_{it} > \bar{y}_{kt}\}$ with $\{\hat{y}_{it} \le \hat{y}_{kt}\}$ and $\{\hat{y}_{it} > \hat{y}_{kt}\}$ based on the estimates, and we find them consistent for all i and t.

In both the symmetric and asymmetric models, we allow the magnitude of learning-by-doing and peer-based learning for new salespeople to differ from those for incumbents. A new salesperson may benefit more from learning, thus having stronger incentives to learn from peers. We classify a salesperson as new for her first three months at the store.[19] We then allow the learning-by-doing and the peer-based learning parameters to be different between new and incumbent salespeople in our models.

5.4. The Consistency of Model Estimation

In this section, we first discuss the data used in estimating our parameters. In the first week of employment, new salespeople have not been exposed to peer-based learning and learning-by-doing. For incumbent salespeople, their initial sales or productivity captures all past learning before our sample period starts. In either case, sales in the first week can be used to estimate the initial ability $\hat{\mathbf{y}}_1$. The identification of the learning-by-doing and forgetting parameters comes from the accumulation of a salesperson's work experience. The former implies that a salesperson's average hourly sales will increase with accumulated work hours, holding other factors constant. On the other hand, forgetting will be inferred if we observe that hourly sales decrease after working for fewer hours in previous period. Salesperson leaves of absence in our data therefore can identify this parameter. Finally, variation in the pool of peers every week will identify peer-based learning within and across counters. This variation is mainly due to the policy of shift assignment at the store. The counter relocation in the middle of our sample period also brings a change in the pool of peers the salesperson faces.

As we stated, the nested optimization procedure that we adopt to estimate our models is an NLS estimator. It differs from a nonlinear simultaneous estimation procedure only in numerical implementation. The criterion functions are the same (i.e., minimizing the sum of squared errors), and the estimates from both procedures are equivalent. Analogous to the identification condition we discussed in §4.1, the consistency of this NLS estimator relies on the random shift assignment in our setting. Let $\mathbf{X}_t$ be the covariates on the right side of Equation (10), including interactions with peers and work hours in all previous weeks. Let θ_0 be the true model parameters including worker fixed effects. The key criterion for the consistency of the NLS estimator is to satisfy the conditional zero mean error condition; i.e., $\mathrm{E}[\boldsymbol{\varepsilon}_t \mid \mathbf{X}_t; \theta_0] = 0$. From the expression of $\boldsymbol{\varepsilon}_t$ (see Equation (11)), we have

$$\begin{aligned}\mathrm{E}[\boldsymbol{\varepsilon}_t \mid \mathbf{X}_t; \theta_0] = {} & \mathrm{E}[\boldsymbol{\tau}_t \mid \mathbf{X}_t; \theta_0] \\ & + \mathrm{E}\left[\sum_{g=1}^{t-1}\left\{\left(\prod_{h=1}^{g}\boldsymbol{\Theta}_{t-h}\right)\cdot \boldsymbol{\tau}_{t-g}\right\}\middle| \mathbf{X}_t; \theta_0\right] \\ & + \mathrm{E}[\boldsymbol{\eta}_t \mid \mathbf{X}_t; \theta_0]. \end{aligned} \tag{12}$$

The random assignment implies that $\boldsymbol{\Theta}_{t-h}$, a deterministic function of past peer interactions, is uncorrelated with $\boldsymbol{\tau}_{t-g}$ under θ_0. Hence, the second component in the above equation can be written as $\sum_{g=1}^{t-1}\{(\prod_{h=1}^{g}(\boldsymbol{\Theta}_{t-h} \mid \mathbf{X}_t; \theta_0)) \cdot \mathrm{E}[\boldsymbol{\tau}_{t-g} \mid \mathbf{X}_t; \theta_0]\}$, in which $\boldsymbol{\Theta}_{t-h}(\cdot)$ denotes that $\boldsymbol{\Theta}_{t-h}$ is a deterministic function of $\mathbf{X}_t$ with a true value of θ_0. Again because of the random assignment, $\mathbf{X}_t$ is uncorrelated with heterogeneous salesperson learning shock $\boldsymbol{\tau}_t$ and $\boldsymbol{\tau}_{t-g}$. The first and second components in Equation (12) therefore are equal to zero. Furthermore, the short-term sales shock $\boldsymbol{\eta}_t$ captures the interaction with contemporary peers in period t. Under the random assignment, contemporary peer interactions are uncorrelated with past peer interactions and past work hours, so the third component in the equation is also equal to zero. Therefore, the conditional expectation $\mathrm{E}[\boldsymbol{\varepsilon}_t \mid \mathbf{X}_t; \theta_0]$ is zero, implying the consistency of our NLS estimator.

To further examine the consistency issue, we run a simulation study. We assume that $\boldsymbol{\tau}$'s and $\boldsymbol{\eta}$'s in Equation (10) are normally distributed and independent from the worker assignment in previous periods. We simulate sales for each salesperson in each period, based on the assumed model parameters and the worker shift assignment in data. Results are reported in Columns (1) and (2) of Table B.1 in Appendix B, showing that our NLS estimates are very close to the "true" parameters.

6. Results

The results from our models are presented in Table 4. The first column presents our symmetric learning model (Model 1). First of all, the ability of peers, both within and across counters, clearly impacts a salesperson's weekly sales growth. This effect is in particular prominent for the newly hired salespeople. Second, the within-counter effect is four to five times greater than the cross-counter effect for new salespeople. This result is consistent with the peer-based learning mechanism: salespeople can more closely observe within-counter peers and solicit active teaching and

[19] We have also tested other specifications (e.g., the first month) and find that results are qualitatively the same.

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Table 4 **Estimation Results for Salesperson Learning Models**

	(1) Model 1	(2) Model 2	(3) Model 3
Dependent variable: *Weekly sales*			
Within-counter			
Newly hired salesperson peer-based learning (symmetric)	0.0696*** (0.0146)		
Existing salesperson peer-based learning (symmetric)	0.0099** (0.0049)		
Newly hired salesperson peer-based learning from superiors		0.0825*** (0.0158)	0.0856*** (0.0191)
Newly hired salesperson peer-based learning from inferiors		0.0100*** (0.0032)	0.0103*** (0.0038)
Existing salesperson peer-based learning from superiors		0.0134*** (0.0062)	
Existing salesperson peer-based learning from inferiors		0.0029 (0.0019)	
Cross-counter			
Newly hired salesperson peer-based learning (symmetric)	0.0151*** (0.0049)		
Existing salesperson peer-based learning (symmetric)	0.0035* (0.0020)		
Newly hired salesperson peer-based learning from superiors		0.0212*** (0.0059)	0.0231*** (0.0074)
Newly hired salesperson peer-based learning from inferiors		0.0033* (0.0018)	0.0035* (0.0020)
Existing salesperson peer-based learning from superiors		0.0037* (0.0019)	
Existing salesperson peer-based learning from inferiors		0.0025 (0.0017)	
Forgetting	0.9917 (0.1638)	0.9908 (0.1629)	0.9979 (0.1577)
Newly hired salesperson learning-by-doing	0.0054*** (0.0014)	0.0055** (0.0014)	0.0057*** (0.0016)
Existing salesperson learning-by-doing	0.0002 (0.0001)	0.0002 (0.0002)	
Number of observations	19,044	19,044	19,044
Month and year dummies	Yes	Yes	Yes
Counter fixed effects	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes

Note. Robust standard errors are clustered at the worker level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

advice. Peer teaching is unlikely to occur across counters since they are competing against one other and are compensated based on sales. Still, the significant cross-counter effect suggests that by closely locating to a competing counter with star salespeople, salespeople can improve their ability and productivity through the observation of competitor sales techniques. Although sales may be immediately hurt because of competition, the long-term benefit for the counter is substantial. In addition, although the effects for new salespeople are much higher, the significant coefficients for existing salespeople imply that there is still opportunity for experienced salespeople to further improve when working with star salespeople.

Our results also show that working longer hours in the prior week will increase a new salesperson's ability, consistent with learning-by-doing. The ability carryover parameter γ is less than but not statistically different from one, suggesting no knowledge depreciation in our context.[20,21] More importantly, our results quantify and show the relative importance of each source of learning. Based on the estimates in Model 1, a new salesperson, after working 40 hours in the first week, experiences an ability growth from learning-by-doing of about 2%. In contrast, if she also worked at the same counter with a peer of twice her ability all the time, her ability would grow by an additional 5%. If there were another peer twice her ability at a competing counter, her ability would further grow by 1%.[22] Given that the worker exit rate is 44% in the data, learning-by-doing alone may not be sufficient to compensate for the high employee turnover. Our findings suggest that the major contributing factor for the observed worker learning curves is peer-based learning.

The second column presents the results from our asymmetric learning model (Model 2). For a robustness check, we also present results from another estimation model (Model 3), where the ability of existing salespeople is assumed to be stable over time. Results for new salesperson learning in the two models are very similar, indicating that our findings of new salesperson learning are robust to the assumption of how existing workers may learn in the workplace. For the ease of exposition, we will only focus on discussing Model 2. The results are largely consistent with Model 1. However, the model shows a substantial asymmetry in the effects from superior versus inferior peers. Superior salespeople have an even greater positive impact on peers' sales growth. Based on the Model 2 estimates, working with a within-counter peer and a cross-counter peer of twice her ability in one week will increase a new salesperson's

[20] This result also helps address an alternative explanation for the positive peer effects we identify: a salesperson may be more motivated to make up for the commission loss if she was paired up with a star peer in the previous week. However, this explanation suggests that the effects from peers should be short term, which is inconsistent with γ being one. Although we cannot completely rule out this alternative explanation, it can at best partially explain our results from a multiperiod dynamic model.

[21] We also note that we are unable to observe lengthy absences in our data, and thus we must remain agnostic on whether forgetting would occur under such circumstances.

[22] According to Equation (6), the percentage of ability growth of a new salesperson after working 40 hours in a week is $\exp[\ln(40) \times 0.0054] - 1 = 2.01\%$. The percentages of ability growth of a new salesperson after working with a within-counter peer of twice her ability all the time in a week and working with a cross-counter peer of twice her ability all the time in a week are $\exp[\ln(2) \times 0.0696] - 1 = 4.94\%$ and $\exp[\ln(2) \times 0.0151] - 1 = 1.01\%$, respectively.

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ability by 6% and 1.5%, respectively. Inferior peers, on the other hand, have a small negative impact on new salespeople.[23] A possible explanation is that new salespeople cannot distinguish high- and low-ability peers. They may learn bad sales techniques by following the practice of the wrong people. In contrast, incumbent salespeople have better information about peers; the effects from inferior peers thus are insignificant. Regression results in §4.2 do not show significant effects from inferior peers, probably because the median split is not a good measure for inferior peers. Many incumbent salespeople whose ability is below the median are still more knowledgeable than new salespeople, and thus the effects are still positive.

6.1. Further Model Extensions and Results on Peer-Based Learning

In this section, we further explore our data to examine whether our findings are indeed driven by peer-based learning. As discussed earlier, the store has four cosmetics brands using TC and seven using IC. Although these incentives cannot be treated as exogenous, they provide insight into the learning mechanism behind productivity growth. To explore this, we separately estimate the asymmetric model for new salespeople for IC and TC counters. Columns (1) and (2) of Table 5 show that own work experience for new salespeople is higher in IC counters than in TC counters. We also observe stronger cross-counter peer effect for IC counters. This is consistent with the explanation that stronger individual incentives in IC counters may increase the learning effort. Although the positive effects from within-counter superiors are similar for the two compensations systems, they may reflect two countervailing incentives. Whereas IC induces salespeople to put more effort on learning, it motivates less effort toward teaching. In contrast, whereas TC motivates peers to actively teach, IC salespeople in general have weaker incentives to devote effort to learn.

The positive effects from within-counter superiors at IC counters help rule out an alternative explanation—the identified productivity growth reflects new salespeople gaining long-term customers when working with high-ability peers. There are strong financial incentives for IC salespeople to compete for customers. Chan et al. (2014) use data from the same source demonstrating that at IC counters, working with superior peers reduces a salesperson's current sales. If sharing customers between salespeople drove our findings, we would not observe the same positive effects from IC counters. Similarly,

Table 5 Estimation Results of Product Category and Compensation Models

Sample	(1) IC counters	(2) TC counters	(3) Skin care	(4) Makeup
	Dependent variable: *Weekly sales*			
Within-counter peer-based learning from superiors	0.0872***	0.0825***	0.1041***	0.0612***
	(0.0191)	(0.0188)	(0.0237)	(0.0165)
Within-counter peer-based learning from inferiors	0.0089*	0.0134***	0.0106***	0.0097***
	(0.0049)	(0.0045)	(0.0037)	(0.0038)
Cross-counter peer-based learning from superiors	0.0324***	0.0107***	0.0056***	0.0588***
	(0.0099)	(0.0038)	(0.0021)	(0.0183)
Cross-counter peer-based learning from inferiors	0.0027*	0.0038*	0.0013	0.0057*
	(0.0016)	(0.0021)	(0.0009)	(0.0032)
Forgetting	1	1	1	1
Learning-by-doing	0.0079***	0.0047***	0.0024***	0.0037***
	(0.0021)	(0.0014)	(0.0007)	(0.0010)
Number of observations	19,044	19,044	19,044	19,044
Month and year dummies	Yes	Yes	Yes	Yes
Counter fixed effects	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes

Notes. The forgetting parameter is constrained to equal 1. Robust standard errors are clustered at the worker level.
$^{*}p < 0.10$; $^{***}p < 0.01$.

customer sharing cannot explain the positive effects from cross-counter peers.

Next, we investigate how knowledge transfer between salespeople depends on job task difficulty. We examine the two cosmetic subcategories, skin care and makeup, discussed in previous sections. Skin care products are much more difficult to sell than makeup. We rerun our asymmetric Model 3 for new salespeople using a salesperson's average hourly skin care and makeup sales as dependent variables. We present these in Columns (3) and (4) in Table 5, respectively. Peer effects remain the most important predictors of weekly productivity gains for both types of products, but the differences in the coefficients suggest that the learning processes are not identical. Within-counter effects from superiors are much stronger for skin care, whereas cross-counter effects from superiors are stronger for makeup.

These results are consistent with the difference between learning based on observing peers and learning through active teaching. Knowledge transfer across firm boundaries is unlikely to involve active teaching given the competition between the firms[24] and is mostly likely to occur through observation. Skin care products are more brand specific, making learning from other counters less feasible. The much stronger within-counter effect, compared with

[23] Given that the difference in ability between an inferior peer and the focal salesperson is negative, a positive coefficient implies that lower peer ability will reduce the ability of the salesperson in future periods.

[24] Social preferences may lead workers to actively help competitors, as in the tournament-based compensation of fruit pickers in Bandiera et al. (2005). Still, there should be less active help across counters.

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the cross-counter effect, suggests that new salespeople need active help from peers to learn how to pitch difficult products to consumers. For makeup products, the magnitude similarity of learning from inside and outside superiors suggests that learning to sell makeup may occur mainly through observation.

An alternative explanation to knowledge transfer is that the improvement in productivity comes from adopting the work ethic of superior peers.[25] If this were the case, however, there would be no reason why the learning effects in makeup and skin care should differ. Since the impact of observing work ethic within counter and across counters is similar for makeup sales, one cannot explain the large difference between these two effects for skin care sales. Suppose observing the work ethic from cross-counter peers is more difficult than from within-counter peers, and hence the cross-counter effect is negligible for the skin care category; we should then also find such asymmetry in the makeup category.[26]

6.2. Qualitative Evidence of Peer-Based Learning

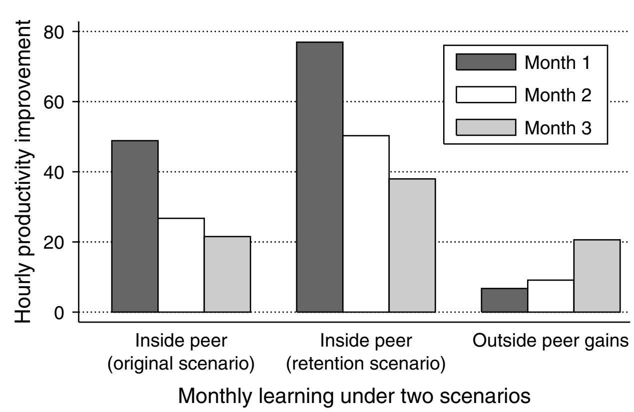
Identifying the causality and mechanisms of peer-based learning in the workplace is challenging as a result of endogeneity issues and unobservable behavior in our data. In the previous sections, we presented evidence that casts doubt on alternative explanations for our estimation results that include customer loyalty, work ethic, and mean reversion. To further support our conclusions, we conducted two focus groups where we interviewed cosmetic salespeople in both our data source store in China and at the Saks Fifth Avenue in Indianapolis, Indiana. The results of these focus groups strongly support our interpretation of teaching and observational learning. Salespeople unanimously indicated acute awareness of the actions of their coworkers at the same counter. Eight of nine interviewees also affirmed their observations of peers at nearby counters. Salespeople repeatedly emphasized the importance of coworkers in learning, particularly for new hires. Many of them argued that management underestimated the importance of the coworkers chosen to work with new hires. Although these studies by no means prove the learning mechanisms that we argue, they are consistent with and complement the evidence provided in our data.

6.3. Counterfactual Experiments

To show the managerial implications of our results, we execute two counterfactual experiments examining how turnover and shift assignment can impact new salesperson ability growth. We first examine turnover, which destroys opportunities for knowledge transfer, and thus productivity growth or maintenance, within the firm (Becker 1962, Ton and Huckman 2008). In our data, a new salesperson A from counter 3 replaces an existing salesperson B in April 2005. Salesperson A's estimated initial ability upon hiring is ¥119.6 per hour. In contrast, B's ability was ¥402.1 per hour in her last week; she is the third most productive salesperson. The left bars under the "Inside peer (original scenario)" in Figure 4 illustrate A's ability growth from the first to the third employment month through peer-based learning, using results from Model 2 in Table 4. Her ability after three months is ¥216.2 per hour and stabilizes after that.

In the alternative scenario, we assume that B is retained and instead another salesperson C with lower ability (¥169.3 per hour) exits, such that the total number of peers remains constant. We assume that B works the same hours as C. The ability growth of A is presented with the middle bars in Figure 4 under "Inside peer (retention scenario)." The total growth in the three months would be ¥165.19 per hour, representing a ¥68.07 per hour higher growth than the original scenario. This effect also extends to competitors. In our example, counter 3 is adjacent to counters 1, 2, and 9 (see Figure 1). In the second month after B leaves, a new salesperson at counter 2

Figure 4 Impact of Retaining a Star Salesperson on Peer Productivity Growth



Note. Outside peer gains reflect difference between original and retention scenarios.

[25] Carrell et al. (2011) find only negative peer effects in work ethic (i.e., fitness), which supports our learning story.

[26] We also estimate a daily-level model to address the aggregation bias concern of using weekly data. Results, presented in Column (1) of Table B.2 in Appendix B, are very similar to those of our weekly model. Another alternative explanation is that location and competition drive our results. To address this, we exploit the exogenous shock of construction outside the department store that forced relocation of all cosmetics counters on November 1, 2004. Figure 1 illustrates how this relocation created a new set of cross-counter peers, and thus new competition, for many of the salespeople. We separately estimate our asymmetric model for the periods before and after the relocation to test for relocation effects, and present the results in Columns (2) and (3) of Table B.2. These models are highly consistent with one another as well as with our main findings in Table 4.

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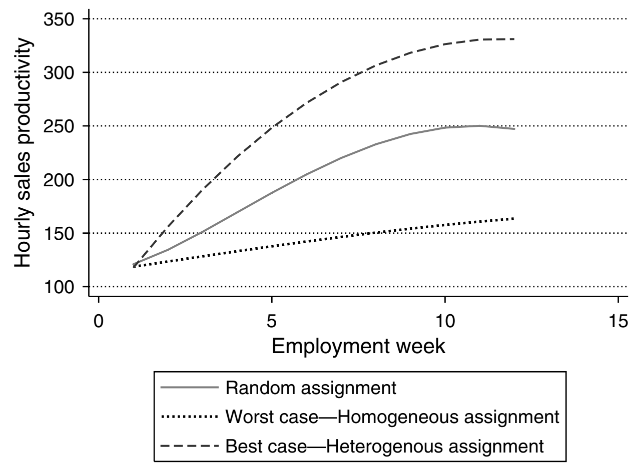
replaces another salesperson, and in the third month another joins at counter 1. By retaining B, the ability of these new salespeople is also enhanced. We calculate the total expected sales revenue of each of the salespeople at counters 1, 2, and 9 who are employed throughout the entire experiment period from the first to the third month. The right bars in Figure 4 show the differences between the original and hypothetical scenarios. The total three-month increased benefits of retaining B for competing counters is ¥36.45 per hour.

This exercise highlights the economic value from retaining high-ability salespeople, not only from their own productivity but also from enhancing peer-based learning for new workers. The total sales increase at counter 3 as a result of learning from B is about 17% of B's own productivity, implying the value of observational learning and teaching from peers (counter 3 uses TC). Since this spillover effect is not fully compensated by commissions, to retain B the brand (manufacturer firm) must offer an extra financial reward (e.g., end-of-year bonus based on annual sales). Furthermore, the sales increase in other counters is about 9% of B's productivity, demonstrating the significance of observational learning (since teaching is unlikely among competing peers). Although the ability growth of outside salespeople does not directly benefit counter 3, the total sales of the cosmetic category likely increase, making this important for the department store. Because this benefit is not rewarded by the brand, the department store may need to offer additional bonuses to retain star salespeople.

If salesperson B cannot be retained, what can the brand do to improve the new salesperson's learning? In the second experiment, we examine the relative performance of different shift assignments and demonstrate their value for learning. We compare three shift assignment scenarios in the first three months (12 weeks) after the new salesperson A from counter 3 is hired. In addition to C, A has two other coworkers in the counter, D and E. The abilities of the four salespeople in the first week are ¥119.6, ¥169.3, ¥266.3, and ¥357.8, respectively. The first scenario randomly assigns the four salespeople into the three shifts, one in shift 1, two in shift 2, and the other one in shift 3, similar to the true store policy. In the second scenario, A is always assigned to work in shift 2 together with E, her peer with the highest ability. Salespeople C and D are rotationally assigned into shifts 1 and 3. Therefore, A is exposed to learning from all peers every day (half of the time she works with C and E, and the other half with D and E). In the last scenario, C and D are always assigned into shift 2, whereas A and E are rotationally assigned into shifts 1 and 3. Thus, A works alone for half of the time and the other half with less productive peers C and D. We assume that shift assignments at other counters are random in all the three scenarios. Figure 5 shows that the ability change of A is remarkably different across the three scenarios, with the difference between the best and the worst cases as large as 94%. Furthermore, by pairing with E, A's total growth in the three months is about ¥200, even higher than the growth from retaining the star salesperson B in the previous experiment.

Figure 5 **Impact of Shift Assignment on New Salesperson Ability Growth**



This exercise illustrates our finding that team heterogeneity has long-term benefit to workers and firms. Compared with the first and last scenarios, staffing a team with a mix of star salespeople and inexperienced rookies can improve peer-based learning over random or homogeneous assignments and thus achieve a much faster growth in sales. This finding is consistent with the empirical results in Hamilton et al. (2003), Mas and Moretti (2009), and Chan et al. (2014), but it suggests a much longer benefit from team heterogeneity, as salesperson A's knowledge and sales in the second scenario will remain at the high level after three months.

7. Discussion and Conclusion

This study identifies individual-level peer-based learning that drives salesperson productivity growth. This occurs both within and across firm boundaries, and their magnitudes depend on the ability of both the source peer and the recipient of the knowledge. It is crucial for a new salesperson to work with more productive workers when she starts. Learning-by-doing also plays a fairly important role. In contrast, forgetting has little impact on the salesperson's productivity growth in our study. To the best of our knowledge, this paper is the first to quantify and decompose the underlying sources of individual learning in a workplace.

Although we cannot assert the mechanism through which learning occurs, the differential importance

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of learning from inside and outside peers suggests that salespeople learn from both observation and the active teaching of peers, with the latter mechanism unlikely to occur across firm boundaries. The difference in the magnitude of learning when selling skin care versus makeup products suggests that active teaching from peers is critical to the learning of difficult tasks, whereas observation of high-ability peers may be sufficient for simpler ones. The relationship between peer-based learning and compensation also suggests that incentives may impact effort toward learning and teaching, although we must be cautious in our interpretation due to endogenous compensation systems. We have also argued that the identified peer-based learning is likely to involve knowledge transfers and does not entirely result from factors such as adopting the work ethic of superior peers, gaining loyal customers, or others.

Future research must explore how job task and workplace characteristics impact the roles of learning-by-doing versus peer-based learning in settings other than cosmetic sales. Learning-by-doing may play a bigger role in more standardized job tasks with fewer parameters and in those where speed and precision are the primary concerns (e.g., farm and factory production). Furthermore, although the retail technology in our data has remained constant throughout the sample period, learning curves may also be influenced by improvements to production processes or technology (Hatch and Mowery 1998).

In addition, we have not been able to fully investigate the conditions that facilitate knowledge transfer between salespeople. Our finding of asymmetric peer-based learning between IC and TC counters suggests that financial incentives may be crucial for salespeople to invest effort in learning and teaching. Other factors that may impact worker interaction include physical proximity and group identity of workers in the same or different firms, individual worker personality, and organizational culture. To what extent these factors facilitate peer-based learning and how they affect firm productivity growth must be addressed by future research.

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Appendix A. Tests of Random Salesperson Assignment

A.1. Establishing Equal Staffing Assignments

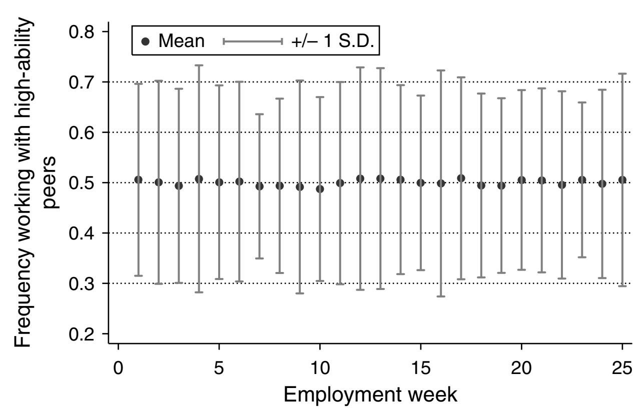
Our empirical models of peer-based learning primarily rely on exogenous variation in peer assignment during new salespersons' initial weeks. (Our models also exploit variation in peer assignment in later weeks, although the magnitude of these effects is much smaller.) We examine the shift assignment pattern, first comparing and testing the difference between the average weekly work hours of new salespeople in their first 12 weeks with that of all other salespeople in the data. Test 1 in Table A.1 shows that the average weekly hours of new salespeople is 41.81, which is not statistically different from the overall average hours of 40.8 ($p = 0.36$). We then test whether the percentage of hours at each shift, for new salespeople in their first 12 weeks, is different from the average in all other data (33% for each shift). Tests 2A (shift 1), 2B (shift 2), and 2C (shift 3) in Table A.1 again reveal no significant differences. We conclude that new salespeople are assigned to shifts in the same way as existing salespeople. Note that the standard deviations of working hours for the three shifts are large, indicating substantial variations in shift assignments across weeks, a condition necessary for the inference of worker learning from the data.

A.2. Establishing the Exogeneity of Peer Assignment

Estimated peer-based learning effects may be biased if the hours that new salespeople work with peers are strategically assigned. For example, if a new salesperson with high learning potential is more likely to be paired with star salespeople, we may wrongly infer that the stars positively influenced her productivity growth. Since the rotating shift assignment equally assigns salespeople to shifts, this endogeneity issue should not exist in our setting.

To verify this independence hypothesis, we first split all salespeople into high- and low-ability categories based on their long-term productivity and the median hourly revenue at each counter. We then examine the percentage of

Figure A.1 **New Salesperson Peer Assignment for Each Employment Week**



Notes. Each bar represents all new salespeople's peers for each week of experience. Not all weeks have equal observations because of attrition and right censoring.

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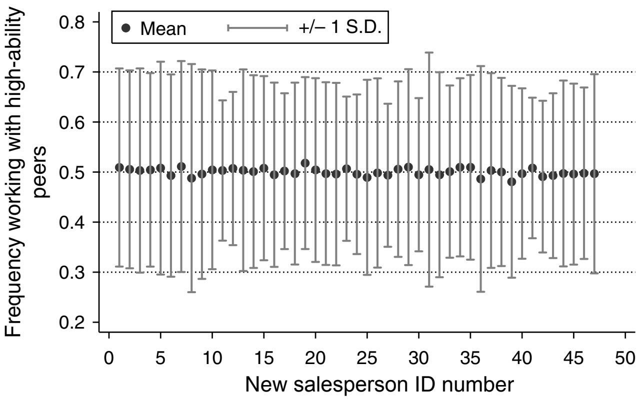
Table A.1 Tests of Equal Staffing Assignments

	Average	S.D.	H_0	T-stat.	P-value
Test 1: Weekly hours for newly hired salespeople	41.81	7.37	40.87	0.93	0.36
Test 2A: Newly hired salespeople assigned to shift 1	34%	11%	33%	1.56	0.12
Test 2B: Newly hired salespeople assigned to shift 2	33%	14%	33%	−1.33	0.18
Test 2C: Newly hired salespeople assigned to shift 3	33%	11%	33%	0.06	0.96

Notes. All values are based on the first 12 weeks for newly hired salespeople. H_0 for Test 1 is based on the average weekly hours for existing salespeople.

Figure A.2 Peer Assignment Across Employment Weeks for Each New Salesperson



Notes. Each bar represents one new salespeople's peers across all weeks. Not all weeks have equal observations because of attrition and right censoring.

hours that a new salesperson works with high- and low-ability salespeople at her counter in the early periods of employment. We present these data in Figure A.1, which shows the mean percentage of hours that new salespeople are assigned to high-ability peers in each of their first 25 weeks of employment. These high-ability peer frequencies consistently average around 50%. To further rule out that salespeople are strategically assigned to high- or low-ability peers, Figure A.2 presents the average time with high-ability peers across all weeks for the 47 new salespeople who stay longer than three months in the data. Again, the averages are very close to 50%, but the standard deviations show considerable variation for any given salesperson, which will be important for identification. Finally, the last two columns in Table A.1 show that the percentage of time new salespeople work with high- and low-ability peers at every counter is near 50%. These figures and tables show that every new salesperson at every counter in every week has an equal chance to work with high-ability and low-ability peers.

We follow this with formal t-tests of differences in the hours that new salespeople work with high- and low-ability peers. Tests 1 and 2 in Table A.2 present the within- and cross-counter test results, showing that when averaged across weeks and across salespeople, the percentages are similar within and across counters. Both tests fail to reject the null hypothesis that the amount of time worked with high-ability peers is the same as the amount worked with low-ability peers.

We further test whether new salespeople are consistently paired with peers based on peer ability. Test 3 in Table A.2 tests whether, conditional on a salesperson working more hours with high-ability within-counter peers in the previous week, the hours with high-ability and low-ability peers in the current week are equal. Test 4 is conditional on working more hours with low-ability within-counter peers in the previous week. Tests 5 and 6 repeat these for peers at adjacent counters. Table A.2 shows that the average hours with either type of peers are statistically indistinguishable, which would not be the case if new salespeople were consistently paired with peers based on their learning potential. For example, if a new salesperson with a high learning potential is more likely to be paired with high-ability peers, we should find a statistically significant difference in Test 3. Consequently, we conclude there is no evidence of strategic scheduling of new salespeople with certain types of peers.

Table A.2 Exogenous Staffing Tests

	High-ability peers		Low-ability peers		H_0 test	
	Mean	S.D.	Mean	S.D.	T-stat.	P-value
Test 1: Hours with inside peers	49.8%	19.3%	50.2%	18.8%	0.37	0.71
Test 2: Hours with outside peers	50.2%	7.6%	49.8%	7.6%	1.02	0.31
Test 3: Hours with inside peers (after working more with high-ability peers in previous week)	42.02	19.17	42.93	17.92	−0.85	0.40
Test 4: Hours with inside peers (after working more with low-ability peers in previous week)	42.75	17.40	41.71	18.44	0.98	0.32
Test 5: Hours with outside peers (after working more with high-ability peers in previous week)	186.00	63.42	180.65	62.36	1.48	0.14
Test 6: Hours with outside peers (after working more with low-ability peers in previous week)	184.50	62.42	182.29	65.21	0.50	0.62

Notes. Tests 1 and 2 are based on the first 12 weeks of sales. All t-tests are of equality between time with high- and time with low-ability peers.

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Appendix B. Summary of Additional Results

Table B.1 Simulation Study Results

	(1) Assumed parameters	(2) Simulation
Dependent variable: *Weekly sales*		
Within-counter		
Newly hired salesperson peer-based learning from superiors	0.08	0.0809*** (0.0023)
Newly hired salesperson peer-based learning from inferiors	0.01	0.0101*** (0.0027)
Existing salesperson peer-based learning from superiors	0.01	0.0099*** (0.0036)
Existing salesperson peer-based learning from inferiors	0.003	0.0028*** (0.0007)
Cross-counter		
Newly hired salesperson peer-based learning from superiors	0.02	0.0198*** (0.0007)
Newly hired salesperson peer-based learning from inferiors	0.003	0.0031*** (0.0002)
Existing salesperson peer-based learning from superiors	0.004	0.0039*** (0.0002)
Existing salesperson peer-based learning from inferiors	0.002	0.0018*** (0.0002)
Forgetting	0.99	0.9902 (0.0119)
Newly hired salesperson learning-by-doing	0.006	0.0061*** (0.0003)
Existing salesperson learning-by-doing	0.0002	0.0002*** (0.0000)
Number of observations	19,044	
Month and year dummies	Yes	
Counter fixed effects	Yes	
Worker fixed effects	Yes	

Note. Robust standard errors are clustered at the salesperson level.
*** $p < 0.01$.

Table B.2 Robustness Tests

	(1) Daily model	(2) Before relocation	(3) After relocation
Dependent variable:	*Daily sales*	*Weekly sales*	*Weekly sales*
Within-counter			
Newly hired salesperson peer-based learning (symmetric)	0.0147*** (0.0052)		
Existing salesperson peer-based learning (symmetric)	0.0026 (0.0018)		
Newly hired salesperson peer-based learning from superiors		0.0891*** (0.0180)	0.0701*** (0.0168)
Newly hired salesperson peer-based learning from inferiors		0.0122** (0.0052)	0.0099* (0.0056)
Existing salesperson peer-based learning from superiors		0.0130* (0.0072)	0.0139** (0.0070)
Existing salesperson peer-based learning from inferiors		0.0026 (0.0021)	0.0032 (0.0021)
Cross-counter			
Newly hired salesperson peer-based learning (symmetric)	0.0032* (0.0017)		
Existing salesperson peer-based learning (symmetric)	0.0009 (0.0007)		
Newly hired salesperson peer-based learning from superiors		0.0227*** (0.0067)	0.0174* (0.0091)
Newly hired salesperson peer-based learning from inferiors		0.0041* (0.0023)	0.0028 (0.0023)
Existing salesperson peer-based learning from superiors		0.0032 (0.0022)	0.0041* (0.0024)
Existing salesperson peer-based learning from inferiors		0.0022 (0.0019)	0.0027 (0.0021)
Forgetting	1.0135 (0.1858)	0.9806 (0.1752)	0.9914 (0.1686)
Newly hired salesperson learning-by-doing	0.0074** (0.0036)	0.0064*** (0.0017)	0.0047*** (0.0013)
Existing salesperson learning-by-doing	0.0003 (0.0003)	0.0002 (0.0003)	0.0002 (0.0002)
Number of observations	133,308	8,648	10,396
Month and year dummies	Yes	Yes	Yes
Counter fixed effects	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes

Note. Robust standard errors are clustered at the salesperson level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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CORRECTION

In this article, "Learning from Peers: Knowledge Transfer and Sales Force Productivity Growth" by Tat Y. Chan, Jia Li, and Lamar Pierce (first published in *Articles in Advance*, March 7, 2014, *Marketing Science*, DOI:10.1287/mksc.2013.0831), the legend in Figure 1 has been corrected.

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