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Compensation and Peer Effects in Competing Sales Teams

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This paper examines how compensation systems impact peer effects and competition in collocated sales teams. We use department store sales data to show that compensation systems influence worker incentives to help and compete with peers within the same firm, which in turn changes the capability of the firm to compete with rivals. Compensation also affects how salespeople impact peers at collocated competing firms, thereby impacting market competition. Moreover, compensation influences how salespeople strategically discount prices in response to peers. Our results suggest that heterogeneity in worker ability enhances firm performance under team-based compensation while hurting individual-based firms and that peer interactions are critical considerations in designing sales force incentive plans and broader firm strategy.

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1. Introduction

The dynamics of worker interaction are critical in determining individual productivity and firm performance. A broad literature in economics and management shows that collocated workers can significantly impact one another's productivity through processes of free riding (Holmstrom 1979), production externalities (Holmstrom 1982), competition (Lazear and Rosen 1981), and monitoring (Knez and Simester 2001). More recent work also shows the importance of skill complementarities (Gant et al. 2002, Ichniowski et al. 2003, Boning et al. 2007) and social pressure or preferences (Bandiera et al. 2005, 2009, 2010; Mas and Moretti 2009). Despite these many mechanisms, empirical studies on peers in the workplace have almost uniformly found positive impacts of high-ability workers on their peers. Mas and Moretti (2009), for example, show that under hourly wages, high-ability grocery checkers increase coworker effort through social processes. Similarly, Azoulay et al. (2010) find that deaths of academic superstars hurt coauthors' publication rates.[1]

Although these studies detail the importance of peers in determining coworker output, they leave several important questions unanswered. First, how might the impact of peers depend on important elements of organizational design such as the compensation system? Economic theory suggests that the incentives embedded in worker compensation might indeed impact worker choices to help, compete with, or sabotage their peers (Drago and Turnbull 1988, Lazear 1989, Itoh 1991, Kandel and Lazear 1992, Siemsen et al. 2007). Existing empirical work has only examined the impact of peers on tasks under a singular compensation system.[2] Second, what is the role of peer interactions in a broader marketplace, where individual coworkers work as teams competing against one another? Since previous research on peer effects has focused exclusively within firms, there is limited guidance on how the impact of peers may extend beyond firm boundaries. Finally, how do workers strategically respond to peers of heterogeneous ability, conditional on their incentives? Although previous studies of peer effects have focused on simple productivity outcomes, we

[1] In contrast, Waldinger (2012) finds no effects from the dismissal of scientific peers in Nazi Germany.

[2] See Prendergast (1999) or Lazear and Shaw (2007) for reviews of worker incentives in firms.

know that incentives from compensation systems can lead to workers gaming the timing and pricing of sales (Oyer 1998, Steenburgh 2008, Misra and Nair 2011, Obloj and Sengul 2012, Chung et al. 2014, Larkin 2014).

In this paper, we address these questions by examining peer interactions in a marketplace where collocated competing firms use different incentive systems to compensate their sales force. Our empirical setting is the cosmetics section in a department store. Multiple brands establish their own counters to compete on a common retail floor, employing salespeople under one of two pay-for-performance compensation systems: team-based (TC) or individual-based (IC) sales commissions. At each counter, salespeople of heterogeneous abilities use selling effort, discounting, and other strategies to compete for the store's customers. In doing so, a salesperson interacts with peers in ways that critically depend on both compensation system and firm boundaries.[3] First, she is motivated to compete with peers from other brands by commission-based compensation. Second, if she works at an IC counter, she also has incentives to compete with peers within her own counter. Third, if she were to alternatively work at a TC counter, she would have incentives to help her within-counter peers if this improves the collective sales of the counter. We use three years of detailed personnel data that identify individual transactions (time, product, quantity and price) and their associated salespeople. Such level of detail allows us to build an empirical model to study how any salesperson's temporal productivity in one period is influenced by the contemporaneous set of peers within and outside the salesperson's counter.

Consistent with prior literature, we define peer effects as the relationship between peer ability and the productivity of coworkers within the same firm (in this case a cosmetics brand/counter). Although other papers have focused on specific mechanisms through which peers influence coworkers (e.g., shame or social pressure in Mas and Moretti 2009), the more general peer effects in our model can include additional mechanisms such as competing and helping that are influenced by the compensation system adopted by the salesperson's counter. In our model, the productivity of salespeople is also affected by peers across the firm boundary at other counters, which we define as strategic effects. Like within-counter peer effects, these strategic effects are also influenced by the compensation system of each firm. We further examine how the impact of peers, both the peer effects and the strategic effects, may be asymmetric; that is, a salesperson may be influenced differently by higher-ability peers than by lower-ability peers. This provides important implications for strategic staffing and compensation decisions by showing how heterogeneity in worker ability can impact total firm performance, and by demonstrating how worker behavior is influenced by the market competition conditions.

Endogeneity is a natural concern in identifying peer effects in field data (Manski 1993). In our setting, we are concerned with two endogeneity issues: staffing decisions by the department store manager and the joint selection of hired salespeople and compensation system by the brand. The first issue is addressed because, to ensure fairness, the department store manager rotates the shifts of salespeople for every counter each day, which results in an equal chance that a salesperson works with any of her peers in any shift. We support this story with statistical tests using data on salesperson shift assignment, showing that there are no systematic differences in the work schedules or peer assignment across salespeople.

To address potential issues of salesperson selection and endogenous compensation choice, we estimate the permanent ability of each salesperson (analogous to the salesperson fixed effect) in the model. Moreover, we collect additional data from a later period where two brands switch compensation systems: one from IC to TC and the other from TC to IC. We show that the direction of peer effects for each brand distinctly changes after the compensation switch in ways consistent with our main results and that the compensation changes do not appear to be accompanied by other policy changes that might confound the effect, such as changes in staffing, pricing, products, or turnover. Results from this quasi-experiment cast doubt on the argument that the endogenous choice of either compensation system or salespeople is driving our results.

Because our model is nonlinear in the interaction of peer and strategic effects with salesperson ability, we propose a new nested nonlinear least squares algorithm to simultaneously estimate model parameters. This algorithm significantly reduces the computational burden of estimating the nonlinear model. The estimation results show that the direction and magnitude of peer impact is critically linked to compensation systems. IC counters produce negative peer effects among salespeople that suggest within-counter competition. Although salespeople lose sales when working with stronger peers of higher ability, stronger salespeople appear to gain customers from lower ability peers. This gain for higher ability salespeople suggests that the loss is not solely driven by sabotage effort from stronger peers, which would be

[3] Throughout the paper, for any cosmetics salesperson, we refer to all other salespeople in our setting as her peers, regardless of whether they work within the same counter, since they have identical job roles and tasks. In our specific setting, we also refer to all salespeople as coworkers since they are collocated.

expected to also detract from those workers' sales productivity. In contrast, working with stronger peers improves salesperson productivity in TC counters. These results are consistent with the existing theory on how team-based incentives can increase peer cooperation or helping (Itoh 1991, 1992, 1993; Kandel and Lazear 1992)[4] and confirm the importance of considering worker coordination in organizational design (Holmstrom and Milgrom 1990). Our results also demonstrate that the link between worker heterogeneity and team performance is highly dependent on the compensation system. Although our results are consistent with previous empirical work (Hamilton et al. 2003, Leonard and Levine 2006, Huckman and Staats 2011), by showing that heterogeneity in salesperson ability improves team performance at TC counters, our results also suggest that at IC counters worker heterogeneity reduces overall sales. This implies that the optimal mix of workers is critically linked to the peer effects generated by the firm's choice of compensation system.

This paper also generates two additional results previously unexplored in the literature. First, we find that peer interactions change the capability of a firm to compete with others in the market. Our results reveal that high-ability salespeople at TC counters have strong negative impacts on outside peers, but high-ability salespeople at IC counters are less likely to impact outside peers, likely because they focus their efforts on competing with inside peers. These findings suggest that although individual compensation may motivate workers, it also transfers much of their competitive effort to within the firm. This may reduce the firm's capability to compete with rivals and, when combined with employees' pricing discretion, may lead to lower profit margins as well. Although endogenous compensation system choices by firms limit our ability to determine whether one compensation system dominates another in profitability, our results suggest that TC produces gains from high-ability salespeople that improve a firm's responsiveness to competition and also reduce the impact of star salespeople in competing firms. Second, we find that salespeople strategically respond to the ability of their peers. Salespeople at IC counters increase price discounting in response to high-ability peers both within and across counters, whereas salespeople at TC counters are less likely to do so. These results have significant implications for firm profitability by suggesting high-ability peers can impact both the sales revenue and the profit margins for other salespeople.

[4] Helping is a general term we use to refer to all efforts that increase peer workers' output, including monitoring, coordination, social pressure, and teaching.

This paper proceeds as follows. Section 2 discusses the empirical setting. Section 3 presents and discusses results for the core symmetric model of the impact of peers. Section 4 presents an asymmetric model with implications for firm performance. The section also discusses a model of salespeople strategically discounting prices in response to peers. Section 5 provides further evidence that addresses endogeneity concerns. Section 6 concludes.

2. Cosmetics Sales in a Department Store

Our empirical setting is cosmetics 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 profits and sells a wide range of products including apparel, jewelry, watches, appliances, electronics, toys, and food. One of its largest categories is cosmetics, where there are 15 major brands occupying separate counters in a common floor area. These brands represent distinct firms that hire their own salespeople to promote and sell their products while paying the department store a share of their revenues. The cosmetics floor effectively becomes an open market, with multiple firms competing for customers in a shared space. This retailing system is a prevalent practice in China and is also common in the U.S. market (Jerath and Zhang 2010, Li et al. 2010).

We observe each individual cosmetics sale for 11 of the 15 counters for 791 days between November 1, 2004, and December 31, 2006. The floor plan and location of these counters during this main time period of our data are presented in Figure 1. Some descriptive statistics for these counters are presented in Tables 1 and 2. Altogether, 61 female salespeople work in one of three overlapping shifts during the seven days per week the department store is open: first (morning) shift from 9 A.M. to 3 P.M., second (afternoon) shift from 12 P.M. to 6 P.M., and third (evening) shift from 3 P.M. to 9 P.M. Although salespeople work an average

Figure 1 Cosmetics Floor Layout in Main Sample Period

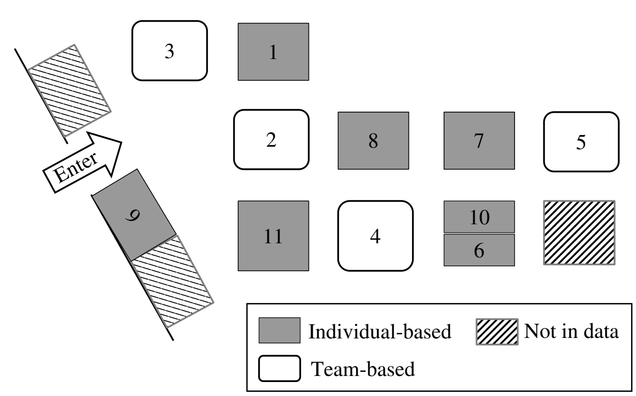


Table 1 Descriptive Statistics of Cosmetic Counters

	Compensation system	Annual sales revenue (US$)	Product price (US$) Min	Max	Mean	Average transaction size (units)	Average discount (%)
Brand 1	IC	631,073	0.142	114.285	19.178	1.961	1.22
Brand 2	TC	626,303	0.120	99.714	15.861	1.618	0.62
Brand 3	TC	553,640	0.108	68.571	12.862	1.650	0.26
Brand 4	TC	229,232	0.285	107.142	16.208	1.787	0.57
Brand 5	TC	108,693	0.130	22.857	7.124	1.537	0.80
Brand 6	IC	142,427	0.114	145.714	15.067	1.638	4.90
Brand 7	IC	285,459	0.142	128.571	23.422	1.455	1.11
Brand 8	IC	43,763	0.142	110.714	17.733	1.672	11.68
Brand 9	IC	195,769	0.190	95.285	18.134	2.340	1.32
Brand 10	IC	133,861	0.238	165.714	20.076	1.813	2.59
Brand 11	IC	128,167	0.142	72.648	16.724	1.574	3.66
IC average		154,908	0.161	119.774	18.526	1.749	4.20
TC average		379,467	0.161	74.571	13.014	1.648	0.60
Total		3,078,387					

Note. US$1 = CN¥ 8.1 on average during our period.

of six hours per day, they often exceed this amount on peak weekends and holidays. Since shifts overlap, salespeople need not work the same shift in a given day to share the counter. The department store manages the arrangement of the counters as well as the staffing of the employees in shifts. For fairness reasons, the store manager typically rotates shifts of each salesperson. For example, if a salesperson works the first shift on Monday, she will be typically assigned to the second or third shift on Tuesday.[5]

There is considerable heterogeneity in the number of employees per counter. The largest brand has 10 salespeople, and the smallest has 3 salespeople (Table 2). Annual sales revenue ranges from $43,763 to $631,073, with product prices from $0.11 to $165.71 (Table 1). We observe multiple salespeople working at a counter in about 70% of shifts. The smaller counters occasionally staff all salespeople simultaneously, likely because salespeople cover multiple shifts on high volume days. There is 18% turnover among the salespeople during our main sample period.

An intriguing aspect of the cosmetics counters in the department store is that team-based and individual-based systems are simultaneously employed by the different brands running each counter. The four brands using TC pay each salesperson a monthly salary of approximately $150 plus 0.5% of the monthly total counter sales. If payments were calculated daily, then salespeople might decide how much to free-ride each day based on the expected productivity of their concurrently scheduled salespeople, but since pay is calculated monthly and salesperson staffing over the month is equally distributed, each salesperson's compensation is based approximately equally on each peer working that month. This means that on any day, the financial motivation for free riding on coworkers should remain independent of concurrently scheduled peers. Still, with whom a salesperson works may be important since monitoring, coordination, specialization, and learning may make skilled coworkers a boon for own individual sales.

The other seven brands use individual-based commissions,[6] compensating salespeople with approximately $150 per month plus 2% of personal monthly sales.[7] IC counters should have less free riding but may suffer from two afflictions. First, despite representing the same brand, coworkers are incentivized to directly compete with one another for customers. Second, salespeople have little incentive to coordinate with or help peers or to work to reduce negative production externalities within the counter. Based on our interviews of local office heads for the brands, some firms choose compensation systems at the national level, whereas others allow regional managers to choose. This choice process is unobservable to us as researchers and may be correlated with brand or salesperson characteristics. Counter-level data presented in Tables 1 and 2 show variation in total sales commissions across counters, based on the total revenues and number of salespeople. TC counters are on average larger than IC counters, suggesting compensation system may not randomly be assigned. On

[5] We provide tests of exogenous peer assignment in §3.2.

[6] The four counters for which we do not have sales data also use individual-based compensation.

[7] On average, about four salespeople were employed by each counter; therefore, 2% of monthly personal sales is comparable to 0.5% of total counter sales.

Table 2 Descriptive Statistics of Cosmetic Sales Teams

	Compensation system	Total salespeople during sample	Salespeople per month		Salespeople per shift		
			Min	Max	Min	Max	Mean
Brand 1	IC	9	5	7	1	5	2.037
Brand 2	TC	10	6	7	1	4	1.786
Brand 3	TC	5	4	4	1	4	1.846
Brand 4	TC	4	3	4	1	4	1.629
Brand 5	TC	5	4	5	1	5	1.753
Brand 6	IC	4	3	3	1	3	1.615
Brand 7	IC	6	4	4	1	3	1.391
Brand 8	IC	4	3	3	1	3	1.195
Brand 9	IC	7	5	5	1	4	1.352
Brand 10	IC	3	3	3	1	3	1.581
Brand 11	IC	4	3	4	1	4	1.783
IC average		5.286	3.714	4.143	1	3.571	1.565
TC average		6.000	4.250	5.000	1	4.250	1.753

average, the commission is about 50% of total income, implying a strong financial incentive for selling.

The nature of sales competition is nuanced by another interesting feature of the department store. During the sample period, all the salespeople had discretion to discount products from their retail prices (Lal 1986, Bhardwaj 2001, Mishra and Prasad 2004). On average, discounting averages about 2.5% of sales revenue across all counters, but this percentage is highly heterogeneous for each counter (see Table 1). This discretionary power is allowed for several reasons. First, haggling over prices is a culturally standard practice in China. Second, it allows skilled salespeople to use personal knowledge to price discriminate and build long-term relationships with customers. Finally, it allows them to better respond to competitor actions and react to temporal market adjustments. Although discretionary discounting may serve several valuable purposes, it also produces potentially problematic incentives (Bhardwaj 2001). Under IC, salespeople may actively discount prices to compete against coworkers, leading to an internecine Bertrand price competition as salespeople within the same counter compete to sell undifferentiated products. Although such price competition may not occur openly through verbal bidding, IC salespeople may offer different discount levels based on the likelihood of customers switching salespeople or returning to purchase at a later date. This contrasts with TC counters, where salespeople decide prices based on cross-counter and not within-counter competition. Table 1 shows that the average discounts at TC counters are lower than those at IC counters. It is important to note that the linear schemes under TC and IC, where salespeople earn a fixed percentage of all sales, reduces the concern of employee temporal gaming at different times of the month.

When an individual salesperson sells products, the cashier records the identity of that salesperson, product types, quantities, prices, transaction time, and level of discounts. This careful sales tracking provides us with detailed information about every cosmetics sale of each of its brands and also the sales of each salesperson in a given shift. The salesperson's productivity depends on a number of factors such as the time of day, day of the week, time of the year, weather, the salesperson's health, types of walk-in customers, and the salesperson's own specific levels of skill or ability. Furthermore, as we have discussed, the salesperson's productivity will also likely depend on the skills and effort of those peers inside and outside counters.

We cannot directly observe salesperson scheduling. Since times of shifts are constant, we assume that if we observe sales for a salesperson during a given shift, the salesperson was also present during other hours in the same shift of that day. Matching hourly sales data with hourly staffing assignments creates identification problems because sales may take a long time to complete. Consequently, the consummation of a sale in a given hour may reflect peer assignments in previous hours, thereby generating noise in any peer effects model. Thus, we will aggregate data to the daily level, as we explain below.[8]

3. Modeling the Impact of Peers

To identify the impact of peers, we model how for any salesperson, the ability of concurrently working salespeople at the same and competing counters

[8] One concern with such a calculation is that salespeople who have not made any transactions in a shift are not counted to be working. The average number of transactions per shift is 10, which is low enough to generate many individual hours without transactions (particularly on low traffic days or early in the morning) but high enough to make a transaction-free shift highly unlikely. This assumption is further supported by the very low number of shifts with only one or two transactions.

influences her temporal productivity.[9] More specifically, we model how peers' ability *relative* to the focal salesperson influences her temporal productivity. In other words, our approach assumes that a high-ability peer influences a salesperson only if that peer is not of equally high ability. We believe that measuring relative, instead of absolute, ability from peers is more reasonable especially when considering competition across counters. Suppose a coworker has average ability. Our relative model allows her impact on a highly productive salesperson to be different from her impact on a relatively unproductive salesperson. Our model also differs from prior models of peer effects in two other ways. First, given our interest in the role of compensation systems, we estimate two separate peer effects—one for each type of counter (IC and TC). Second, we also explore the impact of peers on coworkers at competing counters (i.e., the strategic effects). Again because of our interest in the role of compensation systems, we separately model the strategic effects from competing IC counters on IC counters, competing TC counters on IC counters, competing IC counters on TC counters, and competing TC counters on TC counters.

3.1. A Symmetric Model of Peer Effects and Strategic Effects

Our model starts by specifying how a salesperson's productivity is affected by her peers at the *hour* level. We assume that an individual's productivity is a function of her own permanent productivity and the permanent productivity of all coworkers within and across counters relative to hers. For a salesperson j working for brand i, her productivity in hour h of a day, y_{ijh}, is specified as

$$\begin{aligned} y_{ijh} = {} & \bar{y}_j \\ & + (\gamma_1 \cdot 1\{i \in IC\} + \gamma_2 \cdot 1\{i \in TC\}) \cdot \left[\frac{\sum_{k \in N_{ih}; k \neq j} (\bar{y}_k - \bar{y}_j)}{N_{ih} - 1}\right] \\ & + (\gamma_3 \cdot 1\{i \in IC\} + \gamma_4 \cdot 1\{i \in TC\}) \cdot \left[\frac{\sum_{k' \in N_{i'h}} (\bar{y}_{k'} - \bar{y}_j)}{N_{i'h}}\right] \\ & + (\gamma_5 \cdot 1\{i \in IC\} + \gamma_6 \cdot 1\{i \in TC\}) \cdot \left[\frac{\sum_{k'' \in N_{i''h}} (\bar{y}_{k''} - \bar{y}_j)}{N_{i''h}}\right] \\ & + Z_h \beta + \varepsilon_{ijh}. \end{aligned} \tag{1}$$

In the specification, y_{ijh} is measured by the salesperson's dollar sales in each hour. We measure productivity with dollar sales because salespeople in our setting are compensated based on revenue. In the model, the permanent productivity of the salesperson, $\bar{y}_j$, is a parameter to estimate and is determined not only by the selling capability of the individual but also the quality of the brand's products or locational advantages of the counter on the floor. Furthermore, compensation systems can be an important factor for permanent productivity—if free riding is prevalent under TC, then the average sales of salespeople working for TC counters should be lower than those of IC salespeople. Because of the lack of exogenous changes in our field data, we cannot separately identify these effects in our model.[10] Our approach is to control for all these effects through the salesperson fixed effect $\bar{y}_j$ when estimating the peer and strategic effects.[11]

The second component in the equation captures the peer effects, and the third and fourth capture the strategic effects from IC-based and TC-based competing counters, respectively. The terms $1\{i \in IC\}$ and $1\{i \in TC\}$ are indicators that brand i is either an IC counter or a TC counter. The terms N_{ih}, $N_{i'h}$, and $N_{i''h}$ denote the total number of salespeople working in i's own counter, in competing IC counters, and in competing TC counters at hour h, respectively. We define a counter as competing if it is adjacent to counter i in any direction (e.g., counter 1 in Figure 1 would have three competing counters: 2, 3, and 8).[12] Thus, $[\sum_{k \in N_{ih};\, k \neq j} (\bar{y}_k - \bar{y}_j)/(N_{ih} - 1)]$ represents the average relative permanent productivity of all other active salespeople at salesperson j's counter in hour h, $[\sum_{k' \in N_{i'h}} (\bar{y}_{k'} - \bar{y}_j)/N_{i'h}]$ the average relative permanent productivity of all active peers of IC-based competing counters, and $[\sum_{k'' \in N_{i''h}} (\bar{y}_{k''} - \bar{y}_j)/N_{i''h}]$ the average relative permanent productivity of all peers working for TC-based competing counters in hour h. Parameters γ_1 and γ_2 represent the peer effects for IC and TC counters, respectively. γ_3 and γ_4 measure the strategic effects from salespeople at IC-based competing counters on salespeople at IC and TC counters, respectively. Parameters γ_5 and γ_6 measure the strategic effects from peers who work at TC-based competing counters on salespeople at IC and TC counters, respectively. The vector Z_h represents control variables that may affect sales, including year (years 2 and 3), month (February through December), and day of week (Monday through Saturday). Finally, ε_{ijh} is an error term.

[9] Our empirical model is based on a theoretical framework that models how workers choose to allocate effort toward competing with or helping their peers, given their compensation structure. This model is available from the authors.

[10] This is why we use the term "permanent productivity" in our model specification instead of "ability."

[11] When estimating the model, we normalize the permanent productivity of a salesperson with the median level of average sales in each counter to be zero; thus, $\bar{y}_j$ represents the difference in productivity between salesperson j and the average salesperson of her counter.

[12] Alternative models including distant competing counters show consistent results, with cross-counter strategic effects much smaller from nonadjacent counters. Results are available from the authors.

Specifying the impact of peers at the hour level serves as the building block of our model. According to our interviews with the store management, however, serving a single customer at cosmetics counters can take over an hour. Consequently, sales in an hour may primarily reflect contemporary peer effects from one hour prior or possibly two. Because such frequent sales lags would generate substantial noise in any hourly model, we aggregate the data to the *daily* level for model estimation. Assume that on day t, salesperson j works for T_{jt} hours. Sum up the T_{jt} equations as in Equation (1). With simple algebraic manipulation and letting $\Gamma = (\gamma_1, \ldots, \gamma_6)'$, we have the following:

$$y_{ijh} = x_j(\Gamma)\bar{y}_j + \sum_{k\in i;\, k\neq j} x_k(\Gamma)\bar{y}_k + \sum_{k'\in i'} x_{k'}(\Gamma)\bar{y}_{k'} + \sum_{k''\in i''} x_{k''}(\Gamma)\bar{y}_{k''} + \sum_{h\in T_{jt}} Z_h\beta + e_{ijh}, \qquad (2)$$

where

$$x_j(\Gamma) = T_{jt}\big[1-(\gamma_1\cdot 1\{i\in IC\}+\gamma_2\cdot 1\{i\in TC\}) - (\gamma_3\cdot 1\{i\in IC\}+\gamma_4\cdot 1\{i\in TC\}) - (\gamma_5\cdot 1\{i\in IC\}+\gamma_6\cdot 1\{i\in TC\})\big],$$

$$x_k(\Gamma) = \left[(\gamma_1\cdot 1\{i\in IC\}+\gamma_2\cdot 1\{i\in TC\})\cdot\left(\sum_{h\in T_{kt}\cap T_{jt}} \frac{1}{N_{ih}-1}\right)\right],$$

$$x_{k'}(\Gamma) = \left[(\gamma_3\cdot 1\{i\in IC\}+\gamma_4\cdot 1\{i\in TC\})\cdot\left(\sum_{h\in T_{k't}\cap T_{jt}} \frac{1}{N_{i'h}}\right)\right],$$

$$x_{k''}(\Gamma) = \left[(\gamma_5\cdot 1\{i\in IC\}+\gamma_6\cdot 1\{i\in TC\})\cdot\left(\sum_{h\in T_{k''t}\cap T_{jt}} \frac{1}{N_{i''h}}\right)\right],$$

and $\quad e_{ijh} = \sum_{h\in T_{jt}} \varepsilon_{ijh}.$

Here, i' denotes the set of counter i's IC-based competing counters and i'' the set of i's TC-based competing counters. The notation $h \in T_{lt} \cap T_{jt}$ denotes any hour in which salesperson j and her coworker l work together. Equation (2) is our core model to estimate. Because this model restricts γ's to be the same for effects from higher-ability peers as from lower-ability ones, we also call it a symmetric model.

3.2. Model Identification

The combination of salespeople during any given shift in our data varies considerably. High-ability salespeople are sometimes scheduled with other high-ability salespeople and sometimes with low-ability peers. We use this coworker variation to identify the short-term impact of peers on individual productivity under different compensation systems, as we model in Equation (2). This identification strategy relies on the assumption that salespeople are distributed approximately randomly with peers. Since store managers, not brand managers, decide shifts, there should be no difference across brands. Our interviews with store management revealed that shifts of salespeople are typically rotated on workdays and times because of fairness concerns; salespeople would complain when constantly assigned to unfavorable shifts. This suggests that salesperson assignment is independent of ability, and each salesperson shares shifts with a variety of peers with equal chance.

We verify this using several statistical tests. First, we use a chi-squared test to test the hypothesis that all salesperson pairings are equally frequent. We separately identify all possible salesperson pairings for each counter in every month and compare the number of times each pair of salespeople is assigned together with the expected number of times under the null hypothesis of random shift assignments. The p-value of the test for every counter is substantially higher than 10%, supporting our assertion that salespeople are not systematically scheduled based on ability. To test the existence of type II error (i.e., rejecting unequal pairing frequency when this alternative hypothesis is true), we also calculate the power of the test when the significance level is at 0.1 and the alternative hypothesis is that the pairing frequencies are different at 10% level. The power $(1-\beta)$ of the test is also high for every counter.[13]

Second, we test whether high- or low-ability salespeople, defined by the median split based on the average sales revenue from the data, are more likely to be assigned to specific shifts (morning, afternoon, or evening) or weekends (Saturday and Sunday). The t-tests reject the null hypotheses that high- and low-ability salespeople have different likelihoods of being assigned to each shift or to weekend shifts. High-ability salespeople staff 50.4% of first shifts, 49.8% of second shifts, and 50.3% of third shifts. The p-values testing against equal likelihood (50%) are 0.45, 0.66, and 0.58, respectively. Similarly, high-ability salespeople staff 49.8% of weekday shifts ($p = 0.68$) and 50.3% of weekend shifts ($p = 0.37$). We also obtain high power of these tests at 0.76 (first shifts), 0.90 (second shifts), 0.89 (third shifts), 0.83 (weekday shifts), and 0.65 (weekend shifts). Overall, test results cast considerable doubt on the conjecture that the salespeople in our setting are endogenously staffed based on ability and support our argument of even shift assignment.

The consistency of our peer and strategic effects estimates also requires the exogeneity of the compensation system to the error term in Equation (2). Since the choice of compensation by each firm is

[13] The respective p-values for the chi-squared tests for the 11 brands are 0.64, 0.36, 0.78, 0.22, 0.63, 0.76, 0.82, 0.70, 0.82, 0.49, and 0.53. The powers of tests are 0.87, 0.73, 0.92, 0.71, 0.90, 0.94, 0.97, 0.92, 0.94, 0.85, and 0.88, respectively.

strategic, it is likely to be correlated with salesperson ability and brand quality unobserved to researchers. In our model the fixed effect $\bar{y}_j$ for every salesperson j captures the effects from worker ability and brand quality as well as the impact of TC or IC on free riding. Therefore, the identification condition only requires that the error term, *after controlling for these fixed effects*, is uncorrelated with the difference in abilities between the salesperson and her peers as well as with the compensation systems adopted by own and competing counters. This condition cannot be directly tested because we cannot randomize salespeople and compensation systems in our setup. To test the consistency of model results, however, we collected a supplemental data set from a later period when two brands switched compensation systems. We find the before-and-after comparison to be highly consistent with our results employing cross-brand observations, providing support for the validity of the peer effects and strategic effects estimation. Further details are provided in §5.

3.3. Estimating the Symmetric Model

Equation (2) is a nonlinear model since the fixed effects $\bar{y}$'s interact with the impact of peers represented by the γ's. A straightforward approach would be to estimate all the parameters together using nonlinear search algorithms; however, this method is computationally burdensome due to the large number of parameters (61 $\bar{y}$'s, 6 γ's, and all β's). An alternative estimation strategy, adopted by previous productivity spillover studies (Pierce and Snyder 2008, Mas and Moretti 2009), is to separately estimate the model in two stages. The first stage estimates fixed effects $\bar{y}$'s while accounting for potential peer effects represented by coefficients for all possible coworker combinations in data; in the second stage the estimated fixed effects are inserted into a counterpart of Equation (2) in our model to estimate the γ's. This method is difficult to implement in our study because in the first stage peer effects and strategic effects have to be nonparametrically estimated for each unique combination of coworkers within and cross counters. Because there are hundreds of unique worker combinations in our data, and since many combinations have only a few repeat observations, the first stage estimates of $\bar{y}$'s, peer effects, and strategic effects would have large standard errors that will have a direct consequence on the estimated γ's in the second stage.

We instead propose a more efficient and easily implemented estimation strategy. More specifically, we propose a nested optimization procedure to simultaneously estimate all parameters in Equation (2).[14] The idea comes from the observation that, conditional on the γ's, Equation (2) is linear in $\bar{y}$'s. We therefore start our estimation by choosing some initial values for γ's. Conditional on the γ's, $x_j(\Gamma)$, $x_k(\Gamma)$, $x_{k'}(\Gamma)$, and $x_{k''}(\Gamma)$ in Equation (2) can be calculated, and standard linear methods can be applied to estimate $\bar{y}$'s. Standard numerical minimization routines can then be used as an outside algorithm to estimate γ's. In our implementation, we first choose a set of γ's, then use ordinary least squares (OLS) to estimate $\bar{y}$'s conditional on γ's. We then apply the Nelder and Mead (1965) simplex method to search for γ's that reduce the sum of squared errors from OLS. Convergence is very fast using such routines given that the dimension of γ's is only six in our model. We experiment with different starting values for the γ's to ensure the converged values are not merely at a local minimum.[15] Given that the optimum of such a nonnested algorithm is virtually the same as estimating all parameters using the nonlinear least squares approach, with only the parameter search process as different, standard errors of the estimates can be computed using the latter approach. We compute robust standard errors for our estimated parameters correcting for potential error clustering at the counter level.

3.4. Estimation Results

Column (1) in Table 3 reports the estimated peer effects and strategic effects from our core symmetric model (model 1) discussed in the previous section. The results identify key differences in productivity spillovers between IC and TC counters. Within IC counters, negative within-counter peer effects (γ_1) indicate that a salesperson's productivity drops by 29% of the magnitude of the increased quality her coworkers. This suggests that a better coworker at an IC counter will steal sales from peers at her own counter. In contrast, positive peer effects within TC (γ_2), though small in magnitude and not significant, are consistent with the mechanisms of helping and coordination.

Salespeople also create strategic effects on other peers across counters. Estimates of γ_3 to γ_6 are all significantly negative, showing that the quality of peers at competing counters reduces sales revenue. But the magnitude of these strategic effects is also highly dependent on compensation. Although IC salespeople reduce sales of outside IC peers (γ_3) by 20% of their increased productivity, they have little effect (6%) on

[14] To the best of our knowledge, the only similar approach that has been adopted is "concentrating the log-likelihood function," which is to write down a set of parameters as a function of another set of parameters in the log-likelihood function and then maximize this "concentrated" log-likelihood function based on the latter set of parameters. See Davidson and MacKinnon (1993, pp. 267–269).

[15] We also conduct a simulation study and verify that this algorithm converges to the true parameters.

Table 3 Impact of Peers Within and Across Counters

	(1) Revenue	(2) Revenue	(3) Revenue	(4) Unit sales	(5) Discounting
Within IC counter					
Symmetric (γ_1)	−0.286*** (0.039)	—	—	—	—
From higher (γ_1^a)	—	−0.197*** (0.025)	−0.903*** (0.107)	−0.0013*** (0.000)	0.0780*** (0.0287)
From lower (γ_1^b)	—	−0.028** (0.014)	−0.078* (0.047)	0.0005 (0.0004)	0.0107 (0.0126)
Within TC counter					
Symmetric (γ_2)	0.059 (0.042)	—	—	—	—
From higher (γ_2^a)	—	0.215*** (0.029)	0.305*** (0.071)	0.0024* (0.0013)	−0.0005 (0.0087)
From lower (γ_2^b)	—	−0.008 (0.007)	−0.028 (0.031)	−0.0003 (0.0008)	0.0025 (0.0194)
IC → IC					
Symmetric (γ_3)	−0.195*** (0.031)	—	—	—	—
From higher (γ_3^a)	—	−0.139*** (0.045)	−0.678*** (0.110)	−0.0029*** (0.0005)	0.0431*** (0.0155)
From lower (γ_3^b)	—	−0.060*** (0.016)	−0.038 (0.033)	−0.0025*** (−0.0005)	0.0420*** (0.0150)
IC → TC					
Symmetric (γ_4)	−0.060** (0.028)	—	—	—	—
From higher (γ_4^a)	—	−0.015** (0.006)	−0.202*** (0.059)	−0.0021*** (0.0005)	0.0088 (0.0054)
From lower (γ_4^b)	—	−0.100*** (0.028)	0.056 (0.042)	−0.0041*** (0.0006)	0.0188** (0.0093)
TC → IC					
Symmetric (γ_5)	−0.515*** (0.064)	—	—	—	—
From higher (γ_5^a)	—	−0.384*** (0.056)	−0.810*** (0.141)	−0.0079*** (0.0012)	0.0857*** (0.0298)
From lower (γ_5^b)	—	0.028** (0.012)	−0.191*** (0.046)	−0.0013* (0.0008)	0.0347*** (0.0123)
TC → TC					
Symmetric (γ_6)	−0.217*** (0.048)	—	—	—	—
From higher (γ_6^a)	—	−0.115*** (0.026)	−0.660*** (0.098)	−0.0027*** (0.0009)	0.0156 (0.0133)
From lower (γ_6^b)	—	−0.006 (0.007)	−0.128*** (0.042)	−0.0022*** (0.0007)	0.0083 (0.0062)
Observations	30,162	30,162	30,162	30,162	30,162
R-square	0.318	0.353	0.338	0.324	0.025
Month and year dummies	Included	Included	Included	Included	Included
Worker fixed effects	Included	Included	Included	Included	Included

Notes. Column (3) uses a model based on the absolute ability of coworkers. All other models use relative coworker ability. Robust standard errors clustered at the counter level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

their TC peers (γ_4).[16] Similarly, although the effect of TC salespeople on IC peers (γ_5) is about −52%, this effect is considerably smaller for outside TC peers (γ_6) at −22%. These also mean that TC salespeople have more influence on their outside peers than do IC salespeople (the magnitude of γ_5 is larger than γ_3 and γ_6 is larger than γ_4). An explanation is that salespeople at IC counters focus much of their effort on within-brand competition, leaving little effort for cross-brand competition. In contrast, with no incentive to compete within the brand, TC salespeople can focus more effort on competing with other counters.

[16] A Wald test of the difference is significant with $p = 0.00$. We use Wald tests to test the significance of all differences in the estimated parameters that we discuss here. Test results are all significant at the 0.05 significance level.

4. An Asymmetric Model with Firm Performance Implications

4.1. Modeling Asymmetric Effects

Our model thus far is symmetric in the sense that the γ's when working with stronger peers are the same as those with weaker peers. This would imply that the impact of any two salespeople on one another's productivity would cancel one another, constraining the effect of worker heterogeneity on team productivity to be zero. Consequently, this restriction would eliminate any implications for firm performance. The symmetric specification also cannot address an alternative explanation for the positive within-counter coefficients for TC counters. Since salespeople at TC counters are compensated regardless of who is credited with a sale, high-ability peers may improve coworker sales performance simply because of ambivalent sales recording rather than the helping behavior that we argue is driving the result.

To address these issues, we construct an asymmetric model that allows effect magnitudes from higher-ability peers to differ from those from lower-ability peers. This model allows, for example, a high-ability salesperson to help her low-ability peers and thereby improve overall team competitiveness or alternatively to steal her peers' customers without improving overall productivity. The only difference of this asymmetric model from the symmetric model in Equation (2) is that for each parameter γ_g, $g = 1, \dots, 6$, we now estimate two separate effects, γ_g^a and γ_g^b. The former (latter) represents the within- or cross-counter effect from coworkers with higher (lower) permanent productivity. That is, for a focal salesperson j and her peer k, we estimate γ_g^a if $\bar{y}_j \le \bar{y}_k$ and γ_g^b otherwise. This asymmetric model therefore has 12 γ's. Although the extension is straightforward, our nested nonlinear estimation algorithm cannot be directly applied to this model because the algorithm requires all permanent productivity parameters $\bar{y}$'s to be linear conditional on γ's. We thus employ an additional strategy when using the nested optimization procedure in model estimation. See §A.1 in the appendix for details on estimation of this model.

Column (2) in Table 3 presents the estimates from this asymmetric model (model 2). A positive coefficient from stronger peers means improved productivity since it measures the impact from the positive difference between peers and the focal salesperson. A positive coefficient from weaker peers, however, means reduced productivity (the negative difference between peers and the focal salesperson). Again we find considerable differences in both peer effects and strategic effects across compensation systems. We also find significant asymmetry in the impact from stronger and weaker peers. Within IC counters, stronger coworkers significantly reduce the sales of a weaker salesperson (−0.197), whereas weaker coworkers have a much smaller effect in increasing the performance of a stronger salesperson (−0.028). Peer effects within TC counters are entirely different. Whereas weaker salespeople have little effect on their peers, stronger salespeople dramatically help peer revenue (0.215).[17] Existing theory suggests two reasons for why high-ability workers might be helping peers. It could be cooperation among self-interested agents if the monetary reward through enhanced team performance dominates the cost of her effort (Itoh 1991, 1992, 1993). Additionally, team pay may generate an effort-enhancing norm and thus give high-ability workers an incentive to monitor one another via peer pressure (Kandel and Lazear 1992, Barron and Gjerde 1997). Either way, salespeople's productivity at TC counters is enhanced through positive spillovers from stronger peers.[18] The large asymmetry in peer effects at TC counters also casts considerable doubt that ambivalence in sales recording is primarily driving these positive peer effects.

Cross-counter results also demonstrate differences between IC and TC. Whereas sales of IC salespeople are negatively impacted by stronger salespeople at other IC counters (−0.139), high-ability salespeople at IC counters have little impact on TC counters (−0.015). Conversely, low-ability IC salespeople yield larger gains to competing TC counters (−0.100) than to competing IC counters (−0.060). Similarly, there are strong strategic effects of stronger TC salespeople on IC counters (−0.384). Enigmatically, weaker TC salespeople appear to hurt IC revenue (0.028), although this coefficient is very small. The resistance to high-ability peers is also evident in competition between TC counters because its magnitude (−0.115) is significantly smaller than the strategic effects of stronger TC salespeople on IC counters. These results suggest that high-ability salespeople at TC counters help their peers more than their IC counterparts do; low-ability salespeople at TC counters are less vulnerable to high-ability outside peers because of helping.

[17] This result is in line with the magnitudes found in Falk and Ichino (2006) and Mas and Moretti (2009), where a 10% increase in the average ability of coworkers increases a given worker's effort by 1.7% and 1.5%, respectively.

[18] In fact, our results are difficult to explain without some element of cooperating, helping, or effort-enhancing behavior. If peer effects purely come from learning, sales for each salesperson should stabilize after many months of worker interactions (unless there was considerable forgetting). This is inconsistent with our findings that a salesperson's temporal productivity is strongly influenced by contemporaneous peers. Another potential explanation, mimicry among collocated workers, does not explain why our estimated peer effects differ across compensation systems. Salespeople at IC counters are capable of mimicry as well, yet their negative peer effects show no evidence of this occurring.

4.2. Alternative Specifications of the Asymmetric Model

To provide robustness checks of our model estimation, we explore two alternative specifications of the asymmetric model (model 2). First, instead of specifying that the impact of peers depends on the relative ability between peers and the focal salesperson, model 3 assumes that the asymmetric effects are driven by the *absolute* ability of peers. The estimates from model 3 are presented in column (3) of Table 3. Although the magnitudes of the effects are now different, they are still qualitatively similar to model 2. The results show that a stronger within-counter peer hurts salespeople's productivity at IC counters (−0.903) but helps at TC counters (0.305). Also, although the existence of a stronger salesperson significantly reduces the productivity of salespeople at competing IC counters, the negative impact on competing TC counters is much smaller (e.g., the estimated impact of high-productivity IC salespeople on outside IC salespeople is −0.678, but only −0.202 on outside TC salespeople).

In place of sales revenue, model 4 uses unit sales to measure a salesperson's productivity. Since the average prices of IC and TC counters are quite different, we use unit sales as proxy for productivity to test if our prior results are driven by the price difference. Column (4) in Table 3 presents the estimates from this model. Again, we find the differences in effects between IC and TC counters qualitatively very similar to what we have presented above. All differences in the coefficients between IC and TC remain unchanged. In summary, results from various models show that the differences in the impact of peers across IC and TC counters are quite robust to model specification choices.[19]

4.3. Price Discounting Responses to Peers

An intriguing and important question is what strategies salespeople adopt in response to the peers of heterogeneous ability. Although our data does not allow us to examine all possible strategies used by salespeople, we investigate one that has important implications for firm performance and profitability: price discounting. To do so, we estimate our primary asymmetric model (model 2) replacing daily revenue as the dependent variable with daily discount percentage and using the estimated $\bar{y}$'s from the model 2 estimation. Since $\bar{y}$'s and indicators $\{\bar{y}_j \leq \bar{y}_k\}$ and $\{\bar{y}_j > \bar{y}_k\}$ are treated as data, this price discounting model is linear in terms γ^d's, the parameters representing the impact of peers on discounting strategy. We use a one-sided Tobit model instead of OLS in the estimation because we frequently observe no discounting being offered. Details on this discounting model are presented in §A.2 of the appendix.

We report the estimation results in column (5) of Table 3. The results show that the impact of competition from peers on the level of price discounting depends strongly on the compensation system. Within IC counters, as a response to the existence of stronger peers at the same counter, salespeople change their pricing strategy by offering discounts to customers (0.078). This implies that worker heterogeneity in IC counters reduces revenue not only through reduced unit sales (see results from model 4 in Table 3) but also through excessive price discounting by salespeople with lower productivity. Such discounting does not necessarily imply explicit bidding for customers, however. Instead, it could be that salespeople are more aggressive in their offers toward customers for fear that they will be captured by a higher-ability peer if they continue browsing. Alternatively, salespeople may more aggressively discount when working with higher-ability peers because they anticipate fewer opportunities to sell and thus fear losing those customers with whom they have already engaged. The high-traffic multicounter setting makes managerial monitoring of such behavior difficult. In contrast, we observe no discounting pressure from stronger salespeople within TC counters, which from a firm's profitability perspective should be more beneficial than intra-firm price competition.

Cross-counter results also show a consistent story. High-ability salespeople at IC counters have little impact on TC counters (IC → TC), causing only a slight increase in discounting (0.008). The cross-counter effects of stronger TC peers on IC counters are the largest (TC → IC), causing IC salespeople to dramatically increase discounting (0.086). The resistance of TC counters to high-ability peers at competing counters is also evident in competition between TC counters (TC → TC), with statistically insignificant effects. Collectively, these cross-counter results show that TC counters are better able to defend themselves from competitors' star salespeople, thus avoiding excessive discounting used to retain customers. This suggests that helping and coordination with team-based counters creates better responses to outside competition without relying on price discounting.

4.4. A Numerical Illustration of Competing, Helping, and Potential Sabotage

To examine which individual mechanisms might be driving differences in the impact of peers across compensation systems, we provide a simple numerical exercise using the parameter estimates from the

[19] We also test other specifications accounting for team size and store traffic in the model and find that these factors do not impact our results. We also use daily number of transactions and average revenue per transaction as proxies for productivity and again find similar results. In other words, stronger peers impact both the number of served customers and transaction size in similar ways to revenue. Results are available from the authors upon request.

asymmetric model. As we noted earlier, existing theory argues that incentives influence how peers impact one another through competition (Lazear and Rosen 1981), helping (Drago and Turnbull 1987, 1988; Itoh 1991, 1992, 1993; Kandel and Lazear 1992; Siemsen et al. 2007), and also potential sabotage (Lazear 1989, Chen 2003). We examine these potential mechanisms by comparing two scenarios with different mixes of salesperson ability. These scenarios demonstrate the impact of a star salesperson on individual, counter, and store-level sales, conditional on the compensation system of the focal counter.

We first assume a scenario in which two low-ability salespeople (with $\bar{y} = ¥200$, about the minimum of estimated salesperson fixed effects) at an IC counter A compete with two average-ability salespeople (with $\bar{y} = ¥400$) at a competing IC counter B. We compare this with another scenario where one salesperson is now replaced by a star salesperson (with $\bar{y} = ¥600$, about the maximum of estimated salesperson fixed effects). We find that, first, the aggregate sales of the two counters increase by ¥371 in the latter scenario, implying an elasticity of sales revenue at 0.93 following the improvement of salesperson productivity. This suggests that the store-level demand is not fixed. Instead better salespeople are likely converting walk-through customers to purchasers and also keeping customers with clear cosmetics needs from purchasing at other stores. Second, in the latter scenario, sales at counter A increase by ¥417, implying a brand-level elasticity of 1.15 following salesperson productivity improvement. Furthermore, the comparison also demonstrates competition both across and within counters. Sales at counter B decrease by ¥45, with sales of the low-ability salesperson at counter A also falling by ¥35. These reduced sales cannot be explained by possible sabotage effort from the star salesperson, because her ¥634 in sales is larger than the ¥600 she would have made when working alone.[20] Instead, the larger sales, combined with the smaller sales for her within-counter peer, suggest she is stealing customers. Had she only spent effort on sabotaging peers' selling effort, we should not find an increase in sales.

We repeat the exercise by assuming that counter A is a TC counter with a star salesperson replacing a low-ability salesperson. Results are similar to those above, but sales at counter A increase even more (¥497), at the cost of reduced revenue at counter B (¥132). Since the sales revenue of the star salesperson is ¥636, larger than the sales she can make when working alone, the reduced sales of counter B is mainly due to the cross-counter competition for customers and not the sabotaging effort from the star salesperson. Furthermore, the sales revenue of the low-ability salesperson at counter A will increase by ¥53, consistent with helping or effort enhancing behavior from the star salesperson under the TC system.

[20] We conceptualize sabotage as effort allocated for the objective of reducing the productivity of others, which would be valuable for a worker in a tournament-based setting (e.g. Lazear 1989). Our setting is not tournament based; therefore, time and effort committed to sabotage will not increase the productivity or earnings of the saboteur but rather reduce them.

4.5. Worker Heterogeneity and Team Performance

Using the estimation results from the asymmetric model, we conduct another numerical exercise to illustrate the implications of worker heterogeneity for brand sales and team performance. In the exercise, we focus on four adjacent counters in Figure 1: 2 (TC), 8 (IC), 11 (IC), and 4 (IC). We assume that each counter has four salespeople that must be allocated across two shifts. We assume that salespeople at all of the counters except one have the same permanent productivity of ¥400. The remaining counter has two high-ability salespeople, A and B, with permanent productivity of ¥600 and two low-ability salespeople, C and D, with permanent productivity of ¥200. We consider two scenarios. In the first scenario, the focal counter uses heterogeneous staffing with one high-ability salesperson and one low-ability salesperson at each shift. In the second scenario, the counter uses homogeneous staffing with the high-ability salespeople together. Within each scenario, we further look at two cases: where the focal counter is IC (e.g., counter 8) and where it is TC (e.g., counter 2).

Table 4 reports the calculated sales revenue for the focal counter in each scenario. Worker heterogeneity hurts IC counters, reducing sales from ¥1,403 with homogeneous staffing to ¥1,268 with heterogeneous staffing (10%). In contrast, TC counters benefit from heterogeneity. Although sales in shift 1 when two high-ability salespeople are together generate higher sales, total counter sales from the two shifts increase from ¥1,590 with homogeneous staffing to ¥1,769 with heterogeneous staffing (11%). The results show that benefits from heterogeneity are highly dependent on the compensation scheme. The negative impact on IC counters is consistent with result in Lazear (1989), suggesting that under certain conditions aggressors should be separated from nonaggressors in a team. This is also consistent with prior studies' results on team assignment and worker heterogeneity discussed in §1.

To verify that our team heterogeneity results are not artifacts of our model specification, we employ an additional test of the effect of worker heterogeneity on team performance. We first identify team sales for each three-hour shift in our data and, using

Table 4 **A Numerical Example of Worker Heterogeneity and Brand Sales**

	IC counter		TC counter	
	Heterogeneous	Homogeneous	Heterogeneous	Homogeneous
Shift 1				
Salesperson A	600	600	600	600
Salesperson B	200	600	200	600
Counter sales	634	1,212	884	1,242
Shift 2				
Salesperson C	600	200	600	200
Salesperson D	200	200	200	200
Counter sales	634	190	884	348
Counter sales from both shifts	1,268	1,403	1,767	1,590

the permanent productivities $\bar{y}$'s estimated from our model, calculate each team's heterogeneity during that period. We measure heterogeneity in two ways: the standard deviation in the $\bar{y}$'s of the team's currently scheduled salespeople and the spread between the $\bar{y}$'s of the best and worst current salespeople. Regressing total team sales on these heterogeneity measures and the control variables used in our models, we again find that worker heterogeneity significantly increases team productivity among TC counters (the coefficient is significantly positive) while reducing productivity in IC counters (the coefficient is significantly negative). Magnitudes of the coefficients are similar using either heterogeneity measurement. These results provide evidence that our findings of how worker heterogeneity impacts team performance are not driven by our model specification.

5. Further Evidence of the Impact of Compensation on Peer Interaction

Although §3.2 has cast doubt on some of the alternative explanations for our findings, there are three unresolved concerns in our analysis. First, there may be observable and unobservable (e.g., brand attributes, salesperson characteristics, etc.) factors that contribute to both the choice of compensation system and the effects identified in our model, thereby driving the relationship found in this study. For example, if products at TC counters are more popular and easier to sell than those at IC counters, this could explain why high-ability salespeople at TC counters have a much larger impact on cross-counter peers than high-ability salespeople at IC counters do. Second, since firms select which salespeople to hire and salespeople select which firm to join, the type of salespeople may be systematically different at IC versus TC counters, even after controlling for salesperson fixed effects. This could occur if more helpful salespeople sorted into TC brands, and more competitive salespeople joined IC brands. Third, the relationship between compensation system and impact of peers may be due to possible location-specific effects. In this alternative explanation, differential levels of customer traffic based on the counter locations presented in Figure 1 might be correlated with both the impact of peers and compensation system. Given these issues, our results cannot be safely interpreted as a causal treatment effect even though we observe two such systems operating in simultaneous competition. In this section, we provide evidence to address these concerns.

5.1. Compensation Changes

To provide support for a causal relationship between compensation and the impact of peers, we collected additional data from a time period in 2008 (two years after our main sample period) when two brands changed compensation systems. Brand 1 changed from IC to TC on October 1, and brand 5 switched from TC to IC on May 1. These changes were dictated by the two brands at a regional level and thus did not coincide with any other changes at the department store. Anecdotal evidence suggests that this switch was an unexpected shock to the salespeople, immediately impacting peer interaction in the counters. The store manager explained to us that following brand 5's switch to IC compensation, two of the salespeople had a physical altercation in the break room after accusations of stealing customers.

To formally test whether the compensation changes influenced the impact of peers, we collected sales data for all 11 counters during this period (sample period from January 1, 2008, to December 31, 2008) and estimated the asymmetric within-counter peer effects and cross-counter strategic effects for before and after the compensation change for both switching counters while controlling for the other nine counters. Consequently, we allow the effects γ's in this model to be brand- and period-specific (before and after the switch). Because each of brand 5's neighbors is IC-based, this model estimates only two cross-counter

Table 5 **Impact of Peers Before and After Compensation Changes**

	Brand 1		Brand 5	
	Before (IC)	After (TC)	Before (TC)	After (IC)
Within-counter peer effects				
From higher	−0.399***	0.292***	0.069	−0.264**
	(0.028)	(0.113)	(0.078)	(0.126)
From lower	−0.121*	−0.050	0.029	−0.105*
	(0.071)	(0.053)	(0.113)	(0.059)
Cross-counter strategic effects				
From higher	−0.245***	−0.076*	−0.017*	−0.178**
	(0.055)	(0.041)	(0.009)	(0.082)
From lower	0.009	−0.035	−0.037	−0.036
	(0.009)	(0.042)	(0.031)	(0.029)
No. of competing IC counters	1		3	
No. of competing TC counters	2		0	
Observations	9,850			
R-squared	0.314			

Notes. Regressions include all 11 counters but only estimate effects for the two switching counters. Robust standard errors clustered at the counter level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

strategic effects without distinguishing IC and TC systems. The estimates thus should be interpreted as the strategic effects averaged across all adjacent IC and TC counters. See §A.3 in the appendix for details on the estimation of this model.

We present the estimation results in Table 5. The results for both brands are consistent with our prior results showing that compensation system impacts the direction and magnitude of peer impact. Brand 1's within-counter peer effects from stronger salespeople change from negative to positive after the switch to a TC system. Similarly the within-counter peer effects from stronger salespeople for brand 5 change from positive to negative after the switch to an IC system, although the positive impact under TC is not precisely estimated. We see similar changes for within-counter peer effects from weaker salespeople that are consistent with prior models. Cross-counter strategic effects similarly change in ways consistent with our primary asymmetric model results from column (2) in Table 3. The counter switching to TC, brand 1, becomes less impacted by high-ability salespeople at competing counters. The counter changing to IC, brand 5, becomes more impacted. Fewer coefficients are statistically significant compared with results in Table 3 because of fewer observations, yet the magnitude and direction of changes are comparable with our main findings. Furthermore, the average discounting percentage changes in ways consistent with our discounting model in column (5) of Table 3. The average discount for brand 1 falls from 1.53% to 0.56% after switching from IC to TC, whereas discounts at brand 5 rise from 0.89% to 3.47% when changing from TC to IC.

We repeat our other specifications for the new data, using unit sales and discounting as dependent variables, observing results consistent with our previous results. The impact of higher-ability peers on discounting, for example, changes from positive to zero when brand 1 moves to a TC system, and changes from zero to positive when brand 5 changes to an IC system. Again these results show that the results from our main sample are not purely driven by brand attributes or worker selection.

These results provide strong support for our argument that compensation system influences peer interaction. Because we cannot observe the reason for these changes, however, we cannot claim that they are exogenous, but substantial evidence suggests they did not coincide with other major policy changes that might confound the relationship between compensation system and peer interaction. First, products sold in each counter and regular prices remained similar after the compensation switch,[21] suggesting that there were no simultaneous changes in product or price strategy and that differences in brand popularity cannot explain our core results. Second, the two switching brands were both outliers in terms of sales revenue and counter size: brand 1 was the largest IC counter, and brand 5 was the smallest TC counter. Although these size characteristics may suggest that compensation systems are endogenously chosen to complement counter size, they also allow us to test

[21] Brand 1 increases its portfolio from 113 to 116 products and its average price from \$32.21 to \$33.36. Brand 5 increases its portfolio from 86 to 90 products and its average price from \$16.81 to \$17.22. Given inflation and economic growth levels, these changes are negligible.

whether our results are conditional on this endogenous choice. For example, if the positive peer effects from TC counters are driven by TC brands having higher sales, as an outlier we should not observe the same peer effects for brand 5 before it switched to IC. Likewise we should not observe the negative within-counter peer effects for brand 1 before the switch.

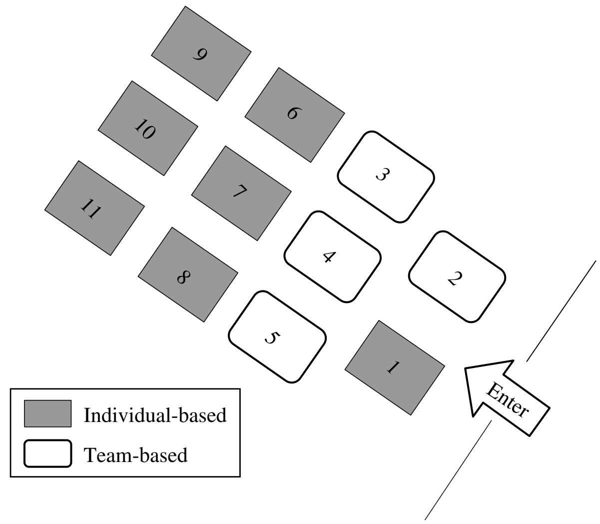
Third, the limited turnover during this period also casts doubt on the concern that our core results can be explained by TC brands endogenously hiring more helpful salespeople. We observe only one salesperson (out of the original seven hired by the two brands) leaving in the months after the compensation changes, an attrition rate similar to the overall sample. Average sales revenue of this salesperson before leaving is equivalent to the average of other peers. If worker selection were explaining our results, we would expect the compensation change to not dramatically impact peer effects, yet this is clearly not the case. Salespeople at brand 1, who were severely hurt by stronger within-counter peers under an IC system, immediately begin benefiting from those same peers after incentives are changed. Still, we acknowledge that there may still be other unobserved factors, such as employee training and internal promotion, that contribute to the findings following the switches in compensation. Our findings, therefore, cannot be treated as proof of the causal relationship between compensation and the impact of peers.

5.2. Counter Relocation

To address the concern that counter location may be driving our results, we collected a third data sample from an earlier time period before the counters were forced to relocate by an exogenous shock outside the department store. On November 1, 2004, the store relocated all cosmetics counters from the east gate area to the west gate area of the first floor. This move was necessitated by city street construction outside the main east entrance, which forced the store to make the west entrance primary. Our primary model results are based on data after this counter relocation (November 1, 2004, to December 31, 2006). Figure 1 illustrates the floor plan of cosmetics counters during our main sample period, whereas Figure 2 presents the old location of the counters before the relocation. Counter 5, a TC brand, moved from near the main entrance in Figure 2 to far away from the entrance in Figure 1. Two IC brands, counters 9 and 11, moved in the opposite direction. We exploit this locational shock to test whether location has a direct impact on the direction and magnitude of peer impact by pooling this third data sample with our main data sample. The new data span the period from January 1, 2003, to December 31, 2006.

We estimate a model on the new data with specific coefficients for each of the three counters both

Figure 2 Cosmetics Floor Layout Prior to Forced Relocation



before and after the counter move. Model details and estimation results are presented in §A.4 of the appendix and Table 6, respectively. Because each of brand 5's neighbors is IC based, this model also estimates only two cross-counter strategic effects without distinguishing IC and TC systems. For all the three brands, we observe very similar within-counter peer effects in the before and after periods, which indicates that counter location has little to do with the relationship between compensation system and peer effects. Strategic effects are consistent in direction but differ in magnitude in ways that support our core model results in Table 3. Brand 5 is less negatively impacted by higher-ability cross-counter peers after relocation. This reduced impact is consistent with our results in column (2) of Table 3 because the relocation moves it away from the fierce competition of TC counter 4 in Figure 1, placing it next to only IC counters shown to have little impact on cross-counter peers. In contrast, both counter 9 and counter 11 suffer much larger negative impacts from stronger cross-counter peers following relocation, which can be explained by moving from a location with only IC competitors to one with two TC competitors. The results from this location model are highly supportive of our initial results and suggest such results are not purely driven by location choices by the store manager.

6. Conclusion

In this paper, we find evidence that compensation systems influence both peer effects within firms as well as strategic effects across firm boundaries. The finding provides unique contributions to the economics, strategy, and marketing literatures. Past theoretical work has examined the relationship between market competition and incentive schemes within firms (e.g.,

Table 6 Impact of Peers Before and After Forced Relocation

	Brand 5		Brand 9		Brand 11	
	Before	After	Before	After	Before	After
Within-counter peer effects						
From higher	0.104***	0.109***	−0.143***	−0.139***	−0.266***	−0.253***
	(0.027)	(0.019)	(0.026)	(0.024)	(0.050)	(0.041)
From lower	0.021*	0.023*	−0.021**	−0.023**	−0.011*	−0.015*
	(0.015)	(0.014)	(0.011)	(0.011)	(0.006)	(0.008)
Cross-counter strategic effects						
From higher	−0.093**	−0.014**	−0.108***	−0.203***	−0.144***	−0.230***
	(0.047)	(0.006)	(0.045)	(0.050)	(0.041)	(0.051)
From lower	−0.023*	−0.027**	−0.071***	−0.035**	−0.083***	−0.015**
	(0.013)	(0.012)	(0.027)	(0.017)	(0.033)	(0.008)
No. of competing IC counters	3	3	3	1	3	2
No. of competing TC counters	1	0	0	2	0	2
Observations			15,782			
R-squared			0.338			

Notes. Regressions include all 11 counters but only estimate effects for the three moving counters. Robust standard errors clustered at the counter level.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Schmidt 1997, Raith 2003, Baggs and de Bettignies 2007, Piccolo et al. 2008, Lacetera and Zirulia 2012) with a focus on agency costs at the managerial or firm level.[22] We show how incentive schemes also impact the choices of workers in groups to either compete with or help and coordinate with peers in their firm, thereby impacting their competitiveness against peers in other firms. This paper therefore studies a different mechanism underlying the relationship between internal incentives and firm competition. Second, we find that the impact of peers is not simply productivity spillovers but also includes likely strategic pricing responses by salespeople. This paper therefore also advances a research stream on complementarities in the multiple strategic choices within firms (Milgrom and Roberts 1990, 1995; Cassiman and Veugelers 2006). Furthermore, we demonstrate that the implications of ability diversity for team productivity and competitiveness depends on compensation policy, a finding that is important given the growing literature on strategic human resource management policies (Ichniowski et al. 1997, Ichniowski and Shaw 1999) and their interaction with other elements of firm strategy (Bloom et al. 2012).

This paper has direct implications for the marketing and economics literatures on sales force management.[23] Most marketing studies of sales force management assume independence among salespeople (e.g., Basu et al. 1985, Coughlan and Sen 1989, Lal and Srinivasan 1993, Joseph and Kalwani 1998, Joseph and Thevaranjan 1998, Godes 2003, Misra et al. 2005).[24] Our study suggests that internal coordination and competition are critical factors in managing sales teams. It is also the first to study how salespeople choose discretionary strategies in response to their coworkers under different compensation systems. Our results show how incentives can impact sales revenue and profit margins through peer interaction, which provides direct managerial implications for firm profitability and sales force incentive plan design (Rao 1990, Mantrala et al. 1994, Raju and Srinivasan 1996, Jain 2012).

This paper also has important implications for internal staffing decisions as well as organizational design and strategy. Although our data are from a department store in China, the organizational design in our setting is common throughout the world for both retail sales organizations as well as in business-to-business (B2B) sales teams.[25] It is also very similar to the inside contracting systems historically prevalent in manufacturing (Buttrick 1952, Bucheli et al. 2010). To the extent that workers exhibit similar responses to incentives regardless of their country of residence and industry, our findings offer broader insights for retail, B2B, and other environments.

We note a few limitations of our study that could be addressed in future research. First, although we

[22] There is also empirical evidence that contract structure can impact firm-level externalities and effort (Gould et al. 2005). Unlike their shopping mall setting, firms in our setting all have identical contracts with the department store, and the contract variation exists at the employee level.

[23] See Albers and Mantrala (2008) or Mantrala et al. (2010) for a review of sales force modeling.

[24] One exception is the literature on sales contests (e.g., Lim et al. 2009).

[25] The cosmetics, apparel, electronics, and toys sections at almost all high-end U.S. department stores (e.g., Bloomingdale's, Neiman Marcus, Nordstrom, and Saks Fifth Avenue) are managed in the same way (Anderson 2005, 2006). See Segalla et al. (2006) for discussions of incentives in B2B sales teams.

have identified the contemporary impact of peers, our model abstracts away from the long-term impact of peers that may result from peer learning through team coordination or competition. A large body of research in management has illustrated that team experience and familiarity can dramatically improve firm performance (Edmondson et al. 2001, Pisano et al. 2001, Huckman et al. 2009). Recent work by Chan et al. (2014) builds on this by showing that individual salespeople can learn from their peers in ways that impact their long-term productivity.[26] Second, like most papers on peer effects there is concern about the reflection problem weakening causal interpretations because peers' productivity levels are simultaneously determined (Manski 1993). This is less of a problem for us since we use permanent productivity as an instrument for temporal ability, but the reflection problem still may exist insomuch as the temporal peer effects over time impact permanent productivity. It is also important to reiterate the potential endogeneity of the compensation systems and worker types chosen by the firms. Although our evidence from the two counters that switch systems supports a causal story, the choice of these counters to switch is also endogenous and may reflect some unobserved factor driving compensation choice. Outside of a true experiment, this problem is difficult to resolve.

We also note that our models restrict the magnitude of both within-counter peer effects and cross-counter strategic effects to the average sales ability of coworkers. Although we believe this restriction is on average appropriate, it does not capture potentially interesting variation in workers' willingness and ability to help. As Oettl (2012) explains, individual productivity and impact on peers are not perfectly correlated, such that some low-ability workers may be highly able or willing to help, whereas other star workers may have little positive impact on peers. Our model does not allow us to capture these two dimensions separately, but future work could attempt to identify such variation in helpfulness at the individual worker level.

In sum, we hope that our rich findings on peer interactions in collocated sales teams will provide useful insights to stimulate future theoretical development, particularly in the context of cross-firm sales competition. We believe theoretically explicating how workers, when working as a group, strategically respond to peers under different incentive schemes and thereby impact firm competition is important for future research. Our empirical findings on how the impact of peers instigates strategic responses from coworkers within and across firms may provide useful insights for modeling such conditions.

[26] See also KC et al. (2013) for evidence of surgeons learning from the past failures of peers.

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Appendix

A.1. Asymmetric Model Estimation
Although the extension from the symmetric model (model 1) to the asymmetric model (model 2) is straightforward, our nested nonlinear estimation algorithm cannot be directly applied to the latter in that the algorithm requires all permanent productivity parameters $\bar{y}$'s to be linear conditional on γ's. With asymmetric effects, $\bar{y}$'s now interact with indicator functions $\{\bar{y}_j \leq \bar{y}_k\}$ or $\{\bar{y}_j > \bar{y}_k\}$, where $k \neq j$. To avoid estimating nonlinearly all 61 $\bar{y}$'s in our asymmetric model we employ a trick in model estimation. Note that to construct the indicators $\{\bar{y}_j \leq \bar{y}_k\}$ or $\{\bar{y}_j > \bar{y}_k\}$, all we need is the productivity ranking for salespeople j and k. This ranking should be consistent with the ranking of salespeople's average sales observed in the data, as long as the impact of peers does not dominate permanent productivity and the shifts of salespeople are truly randomly assigned.

Thus, we use the average daily sales $\hat{y}$ for all salespeople during the sample period to construct $\{\hat{y}_j \leq \hat{y}_k\}$ or $\{\hat{y}_j > \hat{y}_k\}$ and use them as a proxy for indicator $\{\bar{y}_j \leq \bar{y}_k\}$ or $\{\bar{y}_j > \bar{y}_k\}$. Conditional on the ranking, we repeat our proposed nested nonlinear algorithm to estimate the 12 γ's and other parameters. We then compare the ranking of the $\bar{y}$'s estimated from this procedure with the ranking of $\hat{y}$'s. We find that the two rankings are perfectly consistent with each other, which validates that there is no systematic selection issue in shift allocation. To ensure that our estimates are indeed the unique optima that minimize the criterion function value, we estimate the entire nonlinear equation system for all γ's and $\bar{y}$'s using the estimates we obtained as initial values. We find the algorithm always converges to the initial values, showing that our estimates are not just local optima. Since our initial values start at the minima, convergence in this trial exercise is very fast requiring only a few trials.

A.2. Model of Price Discounting as Response to Peers
In a setup similar to our core symmetric model, we run the

following regression for salesperson j working for brand i on day t:

$$\begin{aligned} d_{ijt} = \bar{d}_j &+ (\gamma_1^d \cdot 1\{i \in IC\} + \gamma_2^d \cdot 1\{i \in TC\}) \\ &\cdot \left\{ \sum_{k \in i;\, k \neq j} \left[\left(\sum_{h \in T_{kt} \cap T_{jt}} \frac{1}{N_{ih} - 1} \right) \cdot (\bar{y}_k - \bar{y}_j) \right] \right\} \\ &+ (\gamma_3^d \cdot 1\{i \in IC\} + \gamma_4^d \cdot 1\{i \in TC\}) \\ &\cdot \left\{ \sum_{k' \in i'} \left[\left(\sum_{h \in T_{k't} \cap T_{jt}} \frac{1}{N_{i'h}} \right) \cdot (\bar{y_{k'}} - \bar{y}_j) \right] \right\} \\ &+ (\gamma_5^d \cdot 1\{i \in IC\} + \gamma_6^d \cdot 1\{i \in TC\}) \\ &\cdot \left\{ \sum_{k'' \in i''} \left[\left(\sum_{h \in T_{k''t} \cap T_{jt}} \frac{1}{N_{i''h}} \right) \cdot (\bar{y_{k''}} - \bar{y}_j) \right] \right\} \\ &+ \sum_{h \in T_{jt}} Z_h \beta + \tau_{ijt} \end{aligned} \tag{3}$$

where the dependent variable d_{ijt} represents the salesperson's daily discounting percentage, defined as the ratio of the total amount of discounts offered to customers over the total dollar sales in a day. $\bar{d}_j$ is the fixed effect capturing j's time-invariant discounting due to her ability or propensity, $\bar{y}$'s are the permanent productivities, and γ^d's represent the impact of peers on discounting strategy. We then extend the model to examine how peers with higher and lower ability can heterogeneously influence a salesperson's discounting strategy. The only difference with Equation (3) is that for each effect γ_g^d, where $g = 1, \ldots, 6$, the extended model estimates two separate effects $\gamma_g^{d,a}$ and $\gamma_g^{d,b}$ from peers with higher or lower permanent productivity. Altogether we have 12 γ^d's to estimate. The results reported in Table 3 (column (5)) are from this asymmetric model of price discounting.

A.3. Compensation Change Model

Because there is only one case for each direction of compensation change, we were unable to rerun our full asymmetric model. More specifically, this was because all the surrounding counters of brand 5 are IC-based. Instead, we estimate a simpler version of the asymmetric model with the two switching counters as illustrated in the following equation:

$$\begin{aligned} y_{ijh} = \bar{y}_j &+ (\gamma_{i,b}^{w,h} \cdot 1\{h \in BC\} + \gamma_{i,a}^{w,h} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k \in N_{ih};\, k \neq j} (\bar{y}_k - \bar{y}_j)}{N_{ih} - 1} \right] \\ &+ (\gamma_{i,b}^{w,l} \cdot 1\{h \in BC\} + \gamma_{i,a}^{w,l} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k' \in N_{i'h}} (\bar{y_{k'}} - \bar{y}_j)}{N_{i'h}} \right] \\ &+ (\gamma_{i,b}^{c,h} \cdot 1\{h \in BC\} + \gamma_{i,a}^{c,h} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k'' \in N_{i''h}} (\bar{y_{k''}} - \bar{y}_j)}{N_{i''h}} \right] \\ &+ (\gamma_{i,b}^{c,l} \cdot 1\{h \in BC\} + \gamma_{i,a}^{c,l} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k''' \in N_{i'''h}} (\bar{y_{k'''}} - \bar{y}_j)}{N_{i'''h}} \right] \\ &+ Z_h \beta + \varepsilon_{ijh} \end{aligned} \tag{4}$$

where

- $\gamma_{i,b}^{w,h}$ and $\gamma_{i,a}^{w,h}$ are the peer effects of counter i from within-counter peers with higher ability, before and after the counter changes the compensation system;
- $\gamma_{i,b}^{w,l}$ and $\gamma_{i,a}^{w,l}$ are the peer effects of counter i from within-counter peers with lower ability, before and after the counter changes the compensation system;
- $\gamma_{i,b}^{c,h}$ and $\gamma_{i,a}^{c,h}$ are the strategic effects of counter i from cross-counter peers with higher ability, before and after the counter changes the compensation system;
- $\gamma_{i,b}^{c,l}$ and $\gamma_{i,a}^{c,l}$ are the strategic effects of counter i from cross-counter peers with lower ability, before and after the counter changes the compensation system;
- $1\{*\}$ are indicators—for example, $1\{h \in BC\}$ indicates that the time h belongs to the period before the compensation change.

We estimate the above model by pooling the data of counters 1 and 5 (and their competing counters) from January 1, 2008, to December 31, 2008. Counter 1 has five salespeople and counter 5 has three salespeople during the sample period (their competing counters all together have 26 salespeople). The vector Z_h represents monthly dummies (February through December) and weekday dummies (Monday through Saturday).

A.4. Counter Relocation Model

The regression specification to test the impact of counter relocation is similar to the compensation change model in §A.3. Also for the same reason (i.e., all the surrounding counters of brand 5 are IC-based), we could not run our full asymmetric model. Instead, we estimate a simpler version of the asymmetric model as illustrated in the following equation:

$$\begin{aligned} y_{ijh} = \bar{y}_j &+ (\gamma_{i,b}^{w,h} \cdot 1\{h \in BC\} + \gamma_{i,a}^{w,h} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k \in N_{ih};\, k \neq j} (\bar{y}_k - \bar{y}_j)}{N_{ih} - 1} \right] \\ &+ (\gamma_{i,b}^{w,l} \cdot 1\{h \in BC\} + \gamma_{i,a}^{w,l} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k' \in N_{i'h}} (\bar{y_{k'}} - \bar{y}_j)}{N_{i'h}} \right] \\ &+ (\gamma_{i,b}^{c,h} \cdot 1\{h \in BC\} + \gamma_{i,a}^{c,h} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k'' \in N_{i''h}} (\bar{y_{k''}} - \bar{y}_j)}{N_{i''h}} \right] \\ &+ (\gamma_{i,b}^{c,l} \cdot 1\{h \in BC\} + \gamma_{i,a}^{c,l} \cdot 1\{h \in AC\}) \cdot \left[\frac{\sum_{k''' \in N_{i'''h}} (\bar{y_{k'''}} - \bar{y}_j)}{N_{i'''h}} \right] \\ &+ Z_h \beta + \varepsilon_{ijh} \end{aligned} \tag{5}$$

where

- $\gamma_{i,b}^{w,h}$ and $\gamma_{i,a}^{w,h}$ are the peer effects of counter i from within-counter peers with higher ability, before and after the counter location move;
- $\gamma_{i,b}^{w,l}$ and $\gamma_{i,a}^{w,l}$ are the peer effects of counter i from within-counter peers with lower ability, before and after the counter location move;
- $\gamma_{i,b}^{c,h}$ and $\gamma_{i,a}^{c,h}$ are the strategic effects of counter i from cross-counter peers with higher ability, before and after the counter location move;
- $\gamma_{i,b}^{c,l}$ and $\gamma_{i,a}^{c,l}$ are the strategic effects of counter i from cross-counter peers with lower ability, before and after the counter location move;
- $1\{*\}$ are indicators—for example, $1\{h \in BC\}$ indicates that the time h belongs to the before counter location move region.

We estimate the above model by pooling the data of counters 5, 9, and 11 (and their competing counters) from January 1, 2003, to December 31, 2006. The vector Z_h includes year dummies (2004, 2005, and 2006); monthly dummies (February through December); and weekday dummies (Monday through Saturday).

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