Compensation and Peer Effects in Competing Sales Teams

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Abstract. In retail management, one of the fundamental and critical decisions for managers is how to motivate, staff, and organize their sales force. This task becomes more challenging when employees work in teams so that their productivity will be influenced by peers. Recent work empirically demonstrates peer effects in single-firm work settings under one compensation structure, but these studies leave important questions unanswered. We use a three-year dataset of Chinese cosmetic sales transactions to examine how compensation and firm boundaries influence worker productivity spillovers and sales strategies. We demonstrate three important new sets of findings. First, while high-ability workers under the team-based compensation system significantly improve the sales productivity of their peers, under individual-based compensation they have a strong negative effect on peers while gaining little in the process. Second, we find that peer effects exist across firm boundaries, with workers at team-based compensation counters more capable in competing against peers at other counters. Third, when faced with high-ability peers, workers under individual-based compensation respond by strategically discounting prices offered to customers and focusing on retaining high-value customers who may be more brand loyal. Our results suggest that while heterogeneity in worker productivity enhances total team performance under team-based compensation, it impacts firms with individual-based compensation negatively. This paper provides a unique contribution to the literature by being the first to simultaneously estimate peer productivity spillovers both within and across firms under multiple compensation systems. It is also the first identifying how workers respond to peer effects with discretionary strategies, and provides important implications for managerial decisions on staffing, compensation, and pricing discretion. Finally, the paper implements an improved methodology that generates more efficient estimators than those in previous studies.

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1. Introduction

Co-located workers can significantly impact one another's productivity. These productivity spillovers may be positive, as coordination improves each worker's production through knowledge transfer (e.g. Marshall 1890; Lucas 1988; Berg et al. 1996) and complementarities in skills and abilities (e.g. Boning et al. 2007; Gant et al. 2002, 2003). Yet workers may also negatively impact their peers through the reduced effort of free-riding (e.g. Holmstrom 1979), production externalities from coworkers (e.g. Holmstrom 1982), or competition between peers under the high-powered incentives of pay-for-performance or tournament-based compensation (e.g. Lazear and Rosen 1981). Workers in teams may use social pressure or norms, however, to reduce the cost of free-riding (e.g. Hollander 1990; Kandel and Lazear 1992; Bernheim 1994). Peer effects may also impact other choices of coworkers including the allocation of effort among multiple tasks as well as strategic actions such as discretionary pricing. The many ways in which workers can affect one another provide a simple yet powerful implication – whom you work with matters.

Recent empirical work has documented peer effects in different work settings (e.g. Ichino and Maggi 2000; Falk and Ichino 2006; Bandiera et al. 2007; Mas and Moretti 2009), showing that the quality of peers influences worker behavior and lead to a positive effect of worker heterogeneity on overall team performance (e.g. Hamilton et al. 2003; Mas and Moretti 2009). While these results on peer effects are important, they have been observed exclusively within unique firms or groups and under singular compensation structure. Previous theoretical work suggests great value in studying peer effects under multiple compensation systems, as the direction and magnitude of peer effects may be critically linked to the incentives a firm offers to workers. Kandel and Lazear (1992), for example, show how a partnership structure can provide incentive to reduce free-riding through peer pressure. Itoh (1991) similarly models how compensation structure might induce team members to exert effort toward helping one another. While Holmstrom and Milgrom (1991) present a simple linear model of task allocation in which it is never optimal for two agents to be jointly responsible for any task, Itoh (1992) finds that with some modification it is optimal for an agent to help others and hence to be jointly responsible for each task. Itoh (1993) further develops this theory by showing that principals can better implement cooperation among agents through team-based incentive systems than through individual incentives, while acknowledging that such systems also induce additional free-riding.

Che and Yoo (2001) further show that repeated interactions of agents in long-term can create implicit incentives by encouraging employees' peer sanctioning. The collective implication of these theories is that team-based compensation may provide positive peer effects by inducing voluntary cooperative behavior by individual workers.

In this paper we examine an empirical setting – cosmetic sales in a Chinese department store – which exhibits strong peer effects under different compensation systems. In this store, multiple manufacturers employ salespeople to work at co-located counters on the retail floor. Some of these brand-based counters employ team-based compensation (TC) while others use individual commissions (IC). Salespeople use selling effort, discounting and other discretionary strategies to compete for customers in the store with other salespeople inside and outside the counter. We use a detailed three-year dataset that identifies the individual salesperson, prices, products, and time for each transaction of this period. Such level of detail allows us to build a peer effects model to study how in each period any worker's temporal productivity is influenced by the contemporaneous set of peers within and outside the counter. We allow these peer effects to depend on the compensation systems adopted by the worker's own counter and competing counters. We also allow for asymmetric peer effects where a worker may be influenced differently by superiors (peers with higher permanent productivity) vs. inferiors (peers with lower permanent productivity). We use a nested non-linear least squares algorithm to simultaneously estimate permanent worker productivities and peer effects on concurrently-scheduled salespeople's revenue, unit sales, discounting, and customer mix. This method enables us to study the complicated within-counter and cross-counter peer effects that depend on the compensation systems of both the focal worker and her peers, and to generate estimators that are more efficient than the two-step estimators adopted in previous studies.

Our results are generally consistent with previous literature showing productivity spillovers to coworkers. We find that the direction and magnitude of peer effects are critically linked to compensation systems. IC counters produce negative peer effects among employees that suggest within-counter competition. In particular, salespeople are out-competed by superior peers, yet superior peers do not appear to gain much from lower ability peers. In contrast, working with superior peers will improve worker productivity in TC counters. These results are consistent with existing theory (Itoh 1991, 1992, 1993; Kandel and Lazear 1992; Che and Yoo 2001) on how team-based incentives can increase peer cooperation. In fact, our results are difficult to explain without some element of cooperation or helping behaviors. If peer effects purely come from learning, sales for each worker should stabilize after many months of worker interactions (unless there was considerable forgetting). This is inconsistent with our findings that a worker's temporal productivity is strongly influenced by contemporaneous peers. Another potential explanation, mimicry or imitation among co-located workers, does not explain why our estimated peer effects differ across compensation systems. Workers at IC counters are capable of mimicry as well, yet their negative peer effects show no evidence of this occurring.

Our results are also consistent with existing evidence on worker heterogeneity and performance, although we demonstrate that this effect is highly dependent on compensation system. While heterogeneity in worker ability improves team performance at TC counters as in previous empirical works (e.g. Hamilton et al. 2003; Leonard and Levine 2006; Mas and Moretti 2009), we show that heterogeneity reduces overall sales at IC counters. This implies that the optimal mix of workers may depend on the firm's choice of compensation system.

Besides demonstrating results consistent with existing economic theory, our study generates a set of new findings that leads to several important economic questions unanswered in the previous literature. First, while previous research on peer effects focuses on productivity spillovers, workers in the real workplace may actively respond to peers by employing discretionary strategies to compete with one another. Increased competition from high-ability peers may induce workers to offer lower prices, both when this competition comes from inside and outside the firm. Existing empirical literature shows that incentives can lead to employees gaming the timing and pricing of sales (Oyer 1998; Larkin 2008) and other performance metrics (Asch 1990; Courty and Marschke 2004) across many industries. Similarly, some agency literature demonstrates that agents may allocate effort across multiple tasks in ways that are suboptimal for the principal. Holmstrom and Milgram (1994) and Baker (1992) show that under task-based piece rates, workers may allocate effort to specific tasks in ways that do not account for their complementary nature to the principal. Marx and MacDonald (2001) demonstrate that the magnitude of this "adverse specialization" highly depends on the compensation system offered to the agents. Our results show that workers at IC counters increase price discounting in response to high-ability peers within counters and across competing counters. They also respond by focusing on retaining high-value customers who may be loyal to them and therefore difficult for peers to steal. However, we find that workers at TC counters do not discount prices in response to high-ability peers; instead, they may choose to coordinate in task allocation. High-ability workers may let lower-ability peers serve high-value customers who may be loyal to their brands, while they focus on competing for new customers who may have lower transaction value and are difficult to attract. In the end overall counter sales improves, which is evidenced from our finding that heterogeneity in worker ability improves team performance at TC counters.

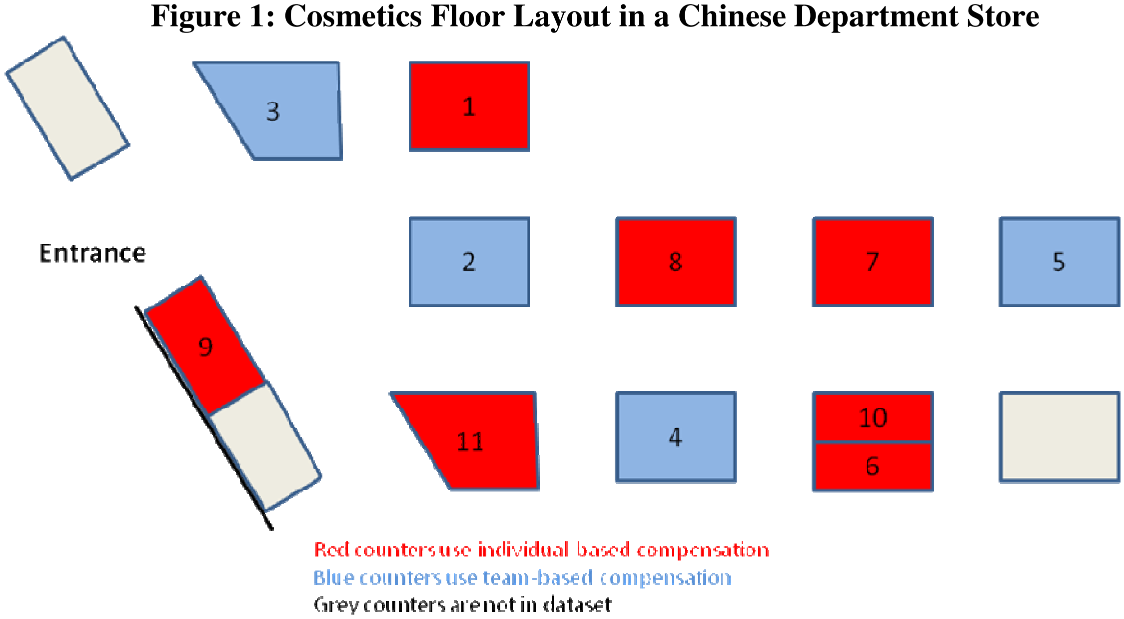
Second, the importance of peer effects may extend beyond the firm boundaries to other organizations through competition. When two competing sales teams are co-located, for example, the high-ability workers in a team are more likely to steal business from the competing team than are low-ability peers. Their competitiveness may also depend on the compensation systems adopted by the teams. We find that high-ability workers at IC counters are less likely to impact outside peers, since the focus of their effort is on competing with inside peers. In contrast, high-ability workers at TC counters have strong negative effects on outside peers, as they can exert the entirety of their effort toward cross-counter competition. Our results suggest that, while individual compensation may motivate workers, it also transfers much of their competitive effort to within the firm. This may reduce the firm's ability to compete with rivals, and when combined with employees' pricing discretion, may lead to lower profit as well. While data constraints limit our ability to determine whether one compensation system dominates another in profitability, our results suggest that TC produces coordination gains that improve a firm's responsiveness to competition, which will reduce the impact of star salespeople in competing brands.

This paper provides a unique contribution to the personnel economics literature by simultaneously estimating peer effects on productivity both within and across firms under multiple compensation systems. It is also the first to study peer effects under discretionary pricing, contributing to the literature on employee gaming behaviors. Our results have important implications for managers of sales groups as well as those providing the marketplaces in which they compete. For instance, we show that worker diversity of skills affects team productivity and competitiveness differently under different compensation systems, a finding that should be important to those studying personnel and organizational economics.

2. Cosmetic Sales in a Chinese Department Store

We study peer effects in the context of team cosmetic sales in a department store in a large metropolitan area in Eastern China. This department store is one of the largest in China in both sales and profit, and sells a wide range of products including apparel, jewelry, watches, home furnishings, appliances, electronics, toys, and food. One of its largest categories is cosmetics, the fifth largest consumer market in China with annual sales of $85 billion in 2004.[1] The department store has 15 major brands in the cosmetics department, with each occupying a counter in the same floor area. These brands hire their own workers 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. The department store manages the arrangement of the counters as well as the staffing of the manufacturers' employees in shifts. We observe each individual cosmetic sale for 11 of the 15 counters over the 2004-2006 period. The floor plan and location of these counters is presented in Figure 1.

Figure 1: Cosmetics Floor Layout in a Chinese Department Store



Sixty-one female salespeople work in one of three overlapping shifts during the seven days per week the department store is open: first shift from 9am to 3pm, second shift from 12pm to 6pm, and third shift from 3pm to 9pm. While workers work an average of six hours per day, they often exceed this amount on peak weekends and holidays. Since shifts are overlapping,

[1] Data from the Victorian Government Business Office.

workers need not work the same shift in a given day to share the counter. Salespeople typically rotate shifts that are assigned by the department store manager. For example, if a salesperson works in the first shift on Monday, she will typically work in the second or third shift on Tuesday. This scheduling process, while not completely random, ensures that each salesperson will rotate workdays and times, and thereby share their shifts with a variety of their peers. In interviews with the department store manager, we learned that there was no strategic scheduling of workers with either certain peers or during specific shifts or days of the week.

One of the interesting aspects of this store is that the individual brands use two different compensation systems: team-based commissions (TC) and individual-based commissions (IC). The four brands using TC pay each worker based on a tiered percentage of the monthly total counter sales. As sales increase, the percentage commission grows. If payments were calculated daily, then workers might decide how much to free-ride each day based on the expected productivity of their concurrently-scheduled workers. But since pay is calculated monthly and worker staffing over the month is equally distributed, each worker'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 worker works may be important since coordination, specialization, and learning may make skilled coworkers a boon for own individual sales. Furthermore, as shown in Mas and Moretti (2009), working with superior workers may create a peer pressure that can reduce the extent of free-riding even without financial motivation.

The other seven brands that we observe use individual-based commissions.[2] In these counters, individual output is recorded and workers are compensated based on an increasing tiered percentage of personal monthly sales.[3] IC counters do not suffer from problems of free-riding, but may suffer instead from two afflictions. First, despite representing the same brand, coworkers are incentivized to directly compete with one another for customers, rather than with competing counters. Second, workers have little incentive to coordinate with or help peers, or to work to reduce negative production externalities within the counter. Thus, in IC counters whom you work with also matters, because they represent your competition and the source of production externalities.

[2] In the case of cosmetics sales, individual workers are technologically independent, and precise measures of individual sales are possible.

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

The nature of sales competition, whether within or across counters, is further nuanced by another interesting feature of the department store. Individual sales people in all counters have discretion to discount products from their retail prices. On average, discounting averages about 2.5% of the daily sales revenues across all counters, but this percentage is highly heterogeneous for each counter (see the last column of Table 1). This discretionary power is allowed for several reasons: Haggling over prices is a culturally standard practice in China important in traditional market settings. Further, it allows skilled salespeople to use personal knowledge to price discriminate and build long-term relationships with customers. It also allows them to better respond to the actions of competitors and react to temporal adjustments in the market. While discretionary discounting may serve several valuable purposes, it also produces potentially problematic incentives. Under IC, workers may actively discount prices to compete against coworkers, leading to an internecine Bertrand price competition as workers within the same counter compete to sell undifferentiated products. This contrasts with TC counters, where workers decide prices based on cross-counter competition. Price competition may be less severe due to the differentiated nature of brand-based cosmetics.

Workers may also increase sales by increasing their selling effort. In an IC counter, workers must allocate a limited amount of effort between competing with peers within their own brand and those at competing counters. In contrast, TC workers can focus all of their effort toward competing with other counters. Salespeople may also discriminate in which customers to serve. For example, a worker may focus her efforts in serving high-value repeat customers, since these customers may have some loyalty specifically to that salesperson.

Cosmetic Sales Data

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

Details of the department store's cosmetic sales are presented in Table 1 and Table 2. Of the eleven counters in our data, four use team-based commissions and seven use individual-based commissions. There is considerable heterogeneity in counter size. The largest brand has ten salespeople, while the smallest has three. Annual sales revenue ranges from $43,763 (US) to $631,073, with product prices from $0.11 to $165.71. Team-based counters generally have larger total sales but lower average prices. Salespeople work alone roughly 30% percent of the time. For the smaller counters we occasionally observe all workers staffed simultaneously. This is likely due to workers staffing multiple shifts on high volume days. We observe sales for 791 days between November 1, 2004 and December 31, 2006. There is 18% turnover among the workers during this period. We cannot directly observe worker scheduling. Since times of shifts are constant, we assume that if we observe sales of a worker during a given shift, the worker was also present during other hours in the same shift of that day.

Since no counters change compensation system during our sample period, we are unable to observe any treatment effect from compensation. Consequently, we cannot analyze whether or not a brand's choice of compensation system is indeed optimal. The focus of our analysis is, conditional on the compensation system, how a salesperson's temporal productivity is affected when her concurrent coworkers change. Similarly, given that we are unable to observe whether the selection of workers into employment with any given brand is random, these results are conditional on the pool of peers hired in the store.

Table 1: Descriptive Statistics of Cosmetic Counters

	Commission Contract	Annual Sales Revenue (US$)	Product Price (US$)			Average Transaction Size (Units)	Average Price Discount
			Min	Max	Mean		
Brand 1	IC	631,073	.142	114.285	19.178	1.961	1.22%
Brand 2	TC	626,303	.12	99.714	15.861	1.618	0.62%
Brand 3	TC	553,640	.108	68.571	12.862	1.650	0.26%
Brand 4	TC	229,232	.285	107.142	16.208	1.787	0.57%
Brand 5	TC	108,693	.13	22.857	7.124	1.537	0.80%
Brand 6	IC	142,427	.114	145.714	15.067	1.638	4.90%
Brand 7	IC	285,459	.142	128.571	23.422	1.455	1.11%
Brand 8	IC	43,763	.142	110.714	17.733	1.672	11.68%
Brand 9	IC	195,769	.190	95.285	18.134	2.340	1.32%
Brand 10	IC	133,861	.238	165.714	20.076	1.813	2.59%
Brand 11	IC	128,167	.142	72.648	16.724	1.574	3.66%
Total		3,078,387					2.61%

Table 2: Team Size

	# of Salesperson	Team Size		
		Min	Max	Mean
Brand 1	9	1	5	2.037
Brand 2	10	1	4	1.786
Brand 3	5	1	4	1.846
Brand 4	4	1	4	1.629
Brand 5	5	1	5	1.753
Brand 6	4	1	3	1.615
Brand 7	6	1	3	1.391
Brand 8	4	1	3	1.195
Brand 9	7	1	4	1.352
Brand 10	3	1	3	1.581
Brand 11	4	1	4	1.783

3. Modeling Peer Effects Within and Across Counters

To identify peer effects, we model how the ability of concurrently working salespeople at the same and competing counters influences the temporal productivity of the worker. Similar to Mas and Moretti (2009), we define ability in terms of permanent productivity, or the fixed effect, of a given worker. Our models differ from prior models of peer effects in three ways. First, we identify how coworkers' ability *relative* to the focal worker influences her temporal productivity. In other words, our approach assumes that a high-ability peer influences a worker only if that peer is not of equally high ability. We believe that measuring relative, instead of absolute, productivity from peers is more reasonable especially when considering competition across counters. Suppose a peer worker has average productivity. Our relative model allows her impact on a highly productive worker to be different from on a relatively unproductive worker.[4] Second, given our interest in the role of compensation systems on the peer effects, we estimate two separate within-counter peer effects for IC and TC counters. Lastly, our model also considers four additional across-counter 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.

[4] We also estimate a model using absolute productivity of peers within and across counters and find that results are qualitatively similar.

3.1 A Symmetric Model Specification

Our model starts with the specification of how a salesperson's productivity is affected by her coworkers at the *hour* level. We assume that an individual's productivity is a function of 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:

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

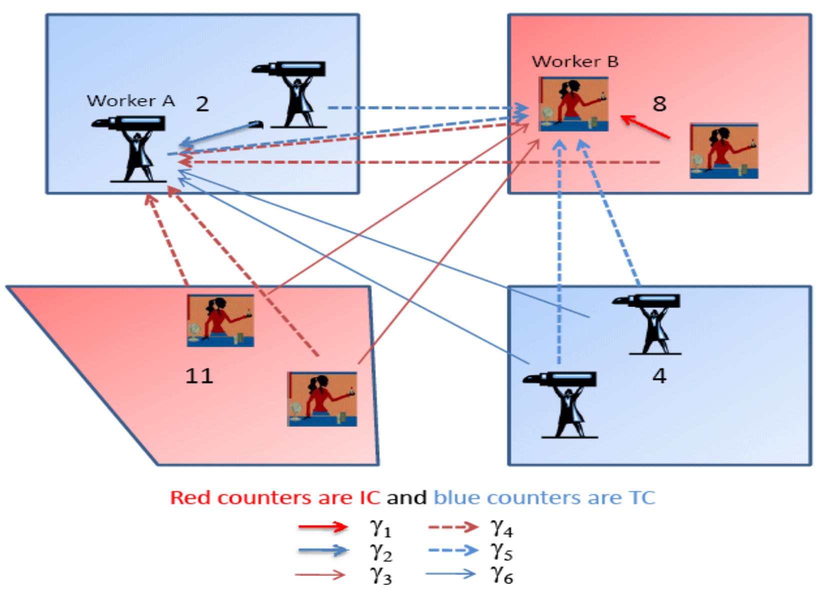
where y_{ijh} is measured by salesperson's dollar sales in each hour. We choose dollar sales to measure productivity because a salesperson in our empirical setting is compensated based on either her revenue sales (in IC counters) or team revenue sales (in TC counters).[5] The worker's permanent productivity or fixed effect $\overline{y_j}$, a parameter to be estimated, captures the worker's selling ability or skill that can also be interpreted as her average hourly dollar sales after controlling for time- and firm-specific factors. The variables $1\{i \in IC\}$ and $1\{i \in TC\}$ are indicators that brand *i* is an IC counter or a TC counter, and N_{ih}, $N_{i'h}$, and $N_{i''h}$ denote the total number of workers working in *i*'s own counter, in competing IC counters, and in competing TC counters at hour *h*, respectively. Thus, $\left[\frac{\sum_{k \in N_{ih}; k \neq j}(\overline{y_k} - \overline{y_j})}{N_{ih} - 1}\right]$ represents the average of the relative permanent productivities of all other active salespeople at worker *j*'s counter in hour *h*, $\left[\frac{\sum_{k' \in N_{i'h}}(\overline{y_{k'}} - \overline{y_j})}{N_{i'h}}\right]$ the average relative permanent productivity of all active peers of IC-based competing counters, and $\left[\frac{\sum_{k'' \in N_{i''h}}(\overline{y_{k''}} - \overline{y_j})}{N_{i''h}}\right]$ the average relative permanent productivity of all peers working for TC-based competing counters, in hour *h*. Z_h is a vector of control variables that may affect sales including year (Year 2 and Year 3), month (February – December), day of week (Monday through Saturday), and brand indicators. Finally, ε_{ijh} is an error term.

[5] Alternatively, unit sales or number of customers served may be used to measure productivity; however, given that price of cosmetic products and total value of transaction across customers vary considerably, such measurements may be very misleading. For example, a high-productivity worker may focus on serving high-value customers or selling high-priced products. Using such measurements may erroneously identify her as having low-productivity.

Peer effects in equation (1) are captured by the parameters γ's. Parameters γ_1 and γ_2 represent the within-counter peer effects for IC and TC counters, respectively. γ_3 and γ_4 measure the peer effects from workers at IC-based competing counters on salespeople at IC and TC counters, respectively. γ_5 and γ_6 measure the peer effects from peers who work at TC-based competing counters on salespeople at IC and TC counters, respectively. Because the model restricts γ's to be the same for peer effects from superiors as from inferiors, we call this a "symmetric" model.

Figure 2 provides a visual representation of the peer effects for four competing counters taken from Figure 1.[6] We represent the peer effects on two focal workers, worker A from counter 2 and worker B from counter 8, from both within and across counters. Blue represents TC counters, while red represents IC counters. Arrows from each worker to the focal workers represent the peer effects based on the permanent productivity of the eight workers. For worker A at TC counter, her peer effects are measured by γ_2 from a within-counter coworker, γ_4 from the average relative productivity of four other co-workers from competing IC counters, and γ_6 from the average relative productivity of two other coworkers from competing TC counters. Similarly the peer effects on worker B at IC counter are measured by γ_1, γ_3, and γ_5.

Figure 2: Within and Across-Counter Peer Effects



[6] A counter is defined as "competing" if it is adjacent to the counter of worker *j* in any direction. For example, counter 1 in Figure 1 would have three competing counters: 2, 3, and 8. We include only adjacent competing counters in all our models. Alternative models with distant competing counters show consistent results, with cross-counter peer effects diminishing with distance between counters.

Specifying how a salesperson's productivity is affected by her coworkers at the hour level serves as the building block of our model. In a market environment like our setting, selling cosmetics product usually takes effort and time.[7] Sales in an hour may only reflect contemporary peer effects in earlier hours. Therefore, we aggregate the data to the *daily* level for model estimation. Assume that on day *t*, salesperson *j* works for T_{jt} hours. We sum up T_{jt} equations as in (1) that becomes the following:

$$
\begin{aligned}
y_{ijt} = \; & T_{jt}\bar{y}_j + (\gamma_1 \cdot 1\{i \in IC\} + \gamma_2 \cdot 1\{i \in TC\}) \cdot \left\{ \sum_{h \in T_{jt}} \left[\frac{\sum_{k \in N_{ih}; k \neq j} (\overline{y_k} - \bar{y}_j)}{N_{ih} - 1} \right] \right\} \\
& + (\gamma_3 \cdot 1\{i \in IC\} + \gamma_4 \cdot 1\{i \in TC\}) \cdot \left\{ \sum_{h \in T_{jt}} \left[\frac{\sum_{k' \in N_{i'h}} (\overline{y_{k'}} - \bar{y}_j)}{N_{i'h}} \right] \right\} \\
& + (\gamma_5 \cdot 1\{i \in IC\} + \gamma_6 \cdot 1\{i \in TC\}) \cdot \left\{ \sum_{h \in T_{jt}} \left[\frac{\sum_{k'' \in N_{i''h}} (\overline{y_{k''}} - \bar{y}_j)}{N_{i''h}} \right] \right\} \\
& + \sum_{h \in T_{jt}} Z_h \beta + e_{ijt} \qquad (2)
\end{aligned}
$$

where $e_{ijt} = \sum_{h \in T_{jt}} \varepsilon_{ijh}$. With simple algebraic manipulation, equation (2) can be re-written as equation (3), where i' denotes the set of counter *i*'s IC-based competing counters, and i'' the set of *i*'s TC-based competing counters, respectively. The notation $h \in T_{lt} \cap T_{jt}$ in (3) denotes the hour in which worker *j* and her coworker *l* working together.

3.2 Estimating the Symmetric Model

Equation (3) is a non-linear model since the salespersons' fixed effects $\bar{y}$'s interact with the peer effects γ's. A straightforward approach would be to estimate all the parameters together using a non-linear search algorithm; however, this method is computationally burdensome due to the large number of parameters (61 $\bar{y}$'s, 6 γ's and all β's) that need to be estimated. An alternative estimation strategy, adopted by some previous productivity spillover studies (e.g. Pierce and Snyder 2008; Mas and Moretti 2009), is to separately estimate the model in two stages. The first stage estimates worker fixed effects $\bar{y}$'s accounting for potential peer effects that are represented by coefficients for the indicators of all possible coworkers combinations in

[7] We learned from an interview with the store manager that serving a single customer can take more than an hour in the store.

data; in the second stage the estimated fixed effects are plugged into a counterpart of equation (3) in our model to estimate the γ's. While this method is simple to implement, applying it to our context raises an efficiency issue. The data requirement to estimate the first stage is very high, since it models the peer effects of all possible combinations of coworkers, within and across counters using a non-parametric approach. Because we only have a limited number of repeat observations for many coworker combinations in our data, we expect the estimates in the first stage to be very imprecise if we apply this method.

$$
\begin{aligned}
y_{ijt} = \Bigg[& T_{jt} - (\gamma_1 \cdot 1\{i \in IC\} + \gamma_2 \cdot 1\{i \in TC\}) \cdot \left(\sum_{k \in i; k \neq j} \sum_{h \in T_{kt} \cap T_{jt}} \frac{1}{N_{ih} - 1} \right) \\
& - (\gamma_3 \cdot 1\{i \in IC\} + \gamma_4 \cdot 1\{i \in TC\}) \cdot \left(\sum_{k' \in i'} \sum_{h \in T_{k't} \cap T_{jt}} \frac{1}{N_{i'h}} \right) \\
& - (\gamma_5 \cdot 1\{i \in IC\} + \gamma_6 \cdot 1\{i \in TC\}) \cdot \left(\sum_{k'' \in i''} \sum_{h \in T_{k''t} \cap T_{jt}} \frac{1}{N_{i''h}} \right) \Bigg] \overline{y_j} \\
& + \sum_{k \in i; k \neq j} \left[(\gamma_1 \cdot 1\{i \in IC\} + \gamma_2 \cdot 1\{i \in TC\}) \cdot \left(\sum_{h \in T_{kt} \cap T_{jt}} \frac{1}{N_{ih} - 1} \right) \right] \overline{y_k} \\
& + \sum_{k' \in i'} \left[(\gamma_3 \cdot 1\{i \in IC\} + \gamma_4 \cdot 1\{i \in TC\}) \cdot \left(\sum_{h \in T_{k't} \cap T_{jt}} \frac{1}{N_{i'h}} \right) \right] \overline{y_{k'}} \\
& + \sum_{k'' \in i''} \left[(\gamma_5 \cdot 1\{i \in IC\} + \gamma_6 \cdot 1\{i \in TC\}) \cdot \left(\sum_{h \in T_{k''t} \cap T_{jt}} \frac{1}{N_{i''h}} \right) \right] \overline{y_{k''}} \\
& + \sum_{h \in T_{jt}} Z_h \, \beta + e_{ijt} \qquad (3)
\end{aligned}
$$

We propose a nested optimization procedure to simultaneously estimate all parameters in equation (3) that is easy to implement and generates estimators more efficient than the two-stage approach. The idea comes from the observation that, conditional on the γ's, equation (3) is linear in $\overline{y}$'s. Specifically, let $\Gamma=(\gamma_1,\ldots,\gamma_6)'$, and let

$$x_j(\Gamma) = [T_{jt} - (\gamma_1 \cdot 1\{i \in IC\} + \gamma_2 \cdot 1\{i \in TC\}) \cdot \left(\sum_{k\in i;k\neq j} \sum_{h\in T_{kt}\cap T_{jt}} \frac{1}{N_{ih}-1}\right)$$

$$-(\gamma_3 \cdot 1\{i \in IC\} + \gamma_4 \cdot 1\{i \in TC\}) \cdot \left(\sum_{k'\in i'} \sum_{h\in T_{k't}\cap T_{jt}} \frac{1}{N_{i'h}}\right)$$

$$-(\gamma_5 \cdot 1\{i \in IC\} + \gamma_6 \cdot 1\{i \in TC\}) \cdot (\sum_{k''\in i''} \sum_{h\in T_{k''t}\cap T_{jt}} \frac{1}{N_{i''h}})] \ ,$$

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

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

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

equation (3) can be re-written as

$$y_{ijt} = x_j(\Gamma)\overline{y_j} + \sum_{k\in i;k\neq j} x_k(\Gamma)\,\overline{y_k} + \sum_{k'\in i'} x_{k'}(\Gamma)\,\overline{y_{k'}} + \sum_{k''\in i''} x_{k''}(\Gamma)\,\overline{y_{k''}} + \sum_{h\in T_{jt}} Z_h\,\beta + e_{ijt} \qquad (4)$$

We therefore start our estimation by choosing some initial values for γ's. Conditional on γ's, standard linear methods can be applied to estimate $\bar{y}$'s. Standard numerical minimization routines then can be used as an "outside" algorithm to estimate γ's. In our implementation, we use OLS to estimate $\bar{y}$'s conditional on γ's, and use the Nelder-Mead (1965) simplex method to search for the optimal γ's that minimize the sum of squared errors as the criterion function value. Convergence is very fast using such routines given that the dimension of γ's is only six in our model. Finally, we compute robust standard errors for our estimated parameters accounting for the existence of heteroscedasticity in error terms e_{ijt}.[8]

3.3 Model Identification

Since none of the counters change pay policies during the period of our data, we are unable to identify how a change in compensation system can alter worker behavior. In contrast, the combination of workers during any given shift varies. High-ability workers are sometimes scheduled with other high-ability workers and sometimes with low-ability peers. We use this variation in the mix of co-scheduled workers to identify short term peer effects on individual and team productivity under different compensation systems.

[8] An implicit assumption of our symmetric model specification is that the number of coworkers on duty does not affect how team members interact with one another. In an alternative specification, we relax this assumption by adding a power term α to capture the possible effect of team size on productivity spillovers. The estimate of α is close to one, suggesting that the size of coworkers plays little role in the magnitude of peer effects.

This identification strategy relies on the assumption that workers are distributed approximately randomly with their peers, that is, high-ability workers have equal chance to be scheduled with low-ability and high-ability peers. While interviews with management suggest that worker assignment is independent of ability, we verify this by using a chi-squared test to test the hypothesis that all worker pairings are equally frequent. We separately identify all possible coworker pairings for each counter in every month, and compare the number of times each pair of worker working together with the expected number of times under the null hypothesis of random shift assignments. Table 3 presents the results, showing that we are unable to reject this null hypothesis at the 10% significance level for any counter, supporting our assertion that workers are not systematically scheduled based on ability.

Table 3: Selection Tests of Worker Assignment

Brand	Pearson's Chi-Square Test Statistic	Degrees of Freedom (*df*)	The 10% Critical Value of the Corresponding *df*	H_0 Rejected?
Brand 1	52.29	126	146.72	No
Brand 2	101.87	137	158.60	No
Brand 3	19.90	75	91.06	No
Brand 4	70.49	74	89.96	No
Brand 5	27.89	61	75.51	No
Brand 6	19.02	63	77.75	No
Brand 7	12.97	59	73.28	No
Brand 8	18.67	50	63.17	No
Brand 9	18.76	85	102.08	No
Brand 10	43.28	70	85.53	No
Brand 11	40.08	69	84.42	No

One might still be concerned that team formation varies across the time of a day. For example, more productive workers may be systematically scheduled to work together when demand spikes upwards. To test this hypothesis we follow Mas and Moretti (2009) to examine the relationship between the number of personnel on duty and the average ability of workers. A positive relationship between the change in personnel and the change in average permanent productivity of workers may suggest that higher ability workers will add to the shift when demand is high. We compare this relationship across consecutive 1-hour periods for each counter, and find little change in the average permanent productivity when the number of workers increases or decreases by one. A t-test reveals that we cannot reject the null hypothesis that there is no change in average productivity at 5% significance level.

3.4 Modeling and Estimating Asymmetric Peer Effects

Our models thus far are "symmetric" in the sense that the γ's when working with superior peers are the same as those with inferior peers. One of the limitations of this symmetric model is that the peer effects of any two workers cancel one another out in the total counter productivity. Consequently, this model provides no implications for the effects of worker heterogeneity on team productivity and hence has no implications for optimal worker mix. To address this question, we construct an asymmetric model of peer effects allowing the magnitudes of effects from superior peers within and across counters to be different from those from inferior peers. This model allows, for example, that a high-productivity salesperson voluntarily helps her low-productivity peers, thereby ending up losing some of her own sales. The only difference of this asymmetric model from the symmetric model in equation (3) is that for each peer effect γ_g, $g = 1, \ldots, 6$, we now estimate two separate effects, γ_g^a and γ_g^b. The former (latter) represents the within- or cross-counter peer effect from coworkers with higher (lower) permanent productivity. That is, for a focal worker *j* and her peer worker *k*, we estimate γ_g^a if $\bar{y}_j \le \bar{y}_k$ and γ_g^b otherwise. Altogether we have 12 γ's.

Though the extension is straightforward, our nested non-linear estimation algorithm cannot be directly applied to this model. The key of using the algorithm is that all permanent productivity parameters $\bar{y}'s$ are linear conditional on γ's. With asymmetric effects, however, $\bar{y}'s$ now interact with indicator functions $\{\bar{y}_j \le \bar{y}_k\}$ or $\{\bar{y}_j > \bar{y}_k\}$, where $k \ne j$. To avoid estimating non-linearly all 61 $\bar{y}'s$ in our model we employ another trick in model estimation. Notice that to construct the indicators $\{\bar{y}_j \le \bar{y}_k\}$ or $\{\bar{y}_j > \bar{y}_k\}$, all we need is the productivity ranking for workers *j* and *k*. Suppose we use the ranking of workers' average sales observed in the data to proxy the ranking of permanent productivities. These two rankings should be consistent with each other if peer effects do not dominate permanent productivity[9] and the shifts of workers are truly randomly assigned. If there is any inconsistency in the rankings this may indicate the existence of systematic selection issues in shift allocation.

[9] In equation (3) this means that the absolute value of γ's applicable to any worker is much smaller than 1.

In model estimation we use the average daily sales $\hat{y}$ for all salespeople during the sample period to construct $\{\widehat{y_j} \leq \widehat{y_k}\}$ or $\{\widehat{y_j} > \widehat{y_k}\}$ as a proxy for indicator $\left\{\bar{y}_j \leq \bar{y}_k\right\}$ or $\left\{\bar{y}_j > \bar{y}_k\right\}$. Conditional on the ranking, we repeat the nested non-linear algorithm as discussed before to estimate the 12 γ's and other parameters. Then we 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 provides another validity support 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 follow up with estimating the whole non-linear equation system for all γ's and $\bar{y}'s$. There we employ the Nelder-Meade simplex method using the estimates we have obtained as initial values. We find the simplex 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 iterations.

4. Estimation Results

Table 4 reports the estimated peer effects from both the symmetric and asymmetric models. We first present the results of our symmetric model, which identify key differences in productivity spillovers between IC and TC counters. Within IC counters, negative within-counter peer effects (γ_1) indicate that a worker's productivity drops by 29% of the increased quality her coworkers. This suggests that a better coworker at 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 only marginally significant, are consistent with specialization or coordination mechanisms.

Peer effects also exist 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 competition peer effects is highly dependent on compensations. While high-productivity IC workers reduce sales of outside IC peers (γ_3) by 20% of their increased productivity, they have little effect (6%) on their TC peers (γ_4). Similarly, while the spillover effect of TC workers on IC peers (γ_5) is about -52%, this peer effect is considerably smaller for outside TC peers (γ_6) at -22%. These also mean that TC workers have more influence on their outside peers than do IC workers (the magnitude of γ_5 is larger than γ_3 and γ_6 larger than γ_4). A possible explanation is that workers 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 workers can focus more effort on competing with other counters.

Table 4: Peer Effect Estimates Within and Across Counters

	(1)	(2)	(3)	(4)	(5)	(6)
	IC Within-Counter Peer Effect (γ_1)	**TC Within-Counter Peer Effect (γ_2)**	**IC Peer Effect on IC (γ_3)**	**IC Peer Effect on TC (γ_4)**	**TC Peer Effect on IC (γ_5)**	**TC Peer Effect on TC (γ_6)**
Symmetric Model						
Symmetric Peer Effects	-.286*** (0.026)	0.059 (0.034)	-.195*** (0.022)	-.060*** (0.023)	-.515*** (0.046)	-.217*** (0.034)
Asymmetric Model						
Effects from Peers with Higher Productivity	-.197*** (0.018)	0.215*** (0.021)	-.139*** (0.040)	-.015*** (0.006)	-.384*** (0.042)	-.115*** (0.021)
Effects from Peers with Lower Productivity	-.028*** (0.011)	-.008 (0.006)	-.060*** (0.014)	-.100*** (0.030)	0.028*** (0.009)	-.006 (0.006)

Robust standard errors are reported in parentheses.

The last two rows in Table 4 present the peer effects estimated from the asymmetric model. A positive coefficient from superior peers means improving productivity as it measures the impact from the positive difference between peers and the focal worker. A positive coefficient from inferior peers means reducing productivity (the negative difference between the peer and the focal worker). Again we find considerable differences in both within- and across-counter peer effects across compensation systems. We also find significant asymmetry in the peer effects from superior- and inferior-ability coworkers. The first column shows that within IC counters superior coworkers significantly reduce the sales of an inferior worker (-.197), while inferior coworkers have a much smaller effect in increasing the performance of a superior worker (-.028). The second column shows a very different story for peer effects within TC counters.

While inferiors have little effect on their peers, superiors dramatically help peer revenue (.215).[10] This result implies that high-ability workers may choose to aid their low-ability peers. 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). Either way, workers' productivity at TC counters is enhanced through positive spillovers from superior peers. While our results for IC and TC counters go in opposite directions, both of them are consistent with previous empirical finding that low productivity workers are more responsive to peer influences than high productivity workers (e.g. Hamilton et al. 2003; Mas and Moretti 2009).

Cross-counter results are consistent with our symmetric model. The third column shows that sales of IC workers are negatively impacted by superiors at other IC counters (-.139), while the fourth column shows that high-ability workers at IC counters have little impact on TC counters (-.015). Conversely, low-ability IC workers yield larger gains to competing TC counters (-.100) than to competing IC counters (-.060). Similarly, the fifth column shows strong competitive peer effects of TC superiors on IC counters (-.384). Enigmatically, TC inferiors appear to hurt IC revenue (.028), although this coefficient is very small. The resistance to high-ability peers is also evident in competition between TC counters, as its magnitude (-.115) is significantly smaller than the competitive peer effects of TC superiors on IC counters. These results suggest that high-ability workers at TC counters have stronger cross-counter peer effects than their IC counterparts, and that TC counters are less vulnerable to high-ability outside peers than IC counters.

Using the estimation results from the asymmetric model, we conduct a numerical exercise based on the four-counter context illustrated in Figure 2. The purpose of this exercise is to illustrate the implications of worker heterogeneity on brand sales. We assume that each of the four counters has four salespeople that must be allocated across two shifts. Salespeople of all of the counters except one have the same permanent productivity at 400. The remaining counter has two high-ability workers, A and B, with permanent productivity of 600 and two low-ability

[10] 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 permanent productivity of coworkers increases a given worker's effort by 1.7% and 1.5%, respectively.

workers, C and D, with permanent productivity of 200. We consider two scenarios. In the first scenario, the focal counter uses heterogeneous staffing where one high-ability worker and one low-ability worker work each shift. In the second scenario, the counter uses homogenous staffing where the high-ability workers work with one another. Within each scenario, we further look at two cases: where the focal counter is IC and where it is TC.

Table 5 reports the calculated dollar sales for the focal counter in each scenario. Worker heterogeneity hurts IC counters, reducing sales from \$1403 with homogeneous staffing to \$1268 with heterogeneous staffing (10 percent). In contrast, TC counters benefit from heterogeneity. Although sales in shift 1 when two high productivity coworkers are together generate higher sales, total counter sales from the two shifts increase from \$1590 with homogeneous staffing to \$1769 with heterogeneous staffing (11 percent). The results on heterogeneity in team-based compensation are consistent with those of Hamilton et al. (2003), but the opposite results on IC teams show that benefits from heterogeneity are highly dependent on the compensation scheme. The latter finding is consistent with result in Lazear (1989), suggesting that under certain conditions "aggressors" should be separated from "non-aggressors" in a team.

Table 5: A Numerical Example of Worker Heterogeneity on Brand Sales

		Individual Based Counter		Team Based Counter	
		Heterogeneous	Homogeneous	Heterogeneous	Homogeneous
Shift 1	Worker A	600	600	600	600
	Worker C	200	600	200	600
	Counter Sales of Shift 1	634	1212	884	1242
Shift 2	Worker B	600	200	600	200
	Worker D	200	200	200	200
	Counter Sales of Shift 2	634	190	884	348
	Counter Sales from 2 Shifts	**1268**	**1403**	**1767**	**1590**

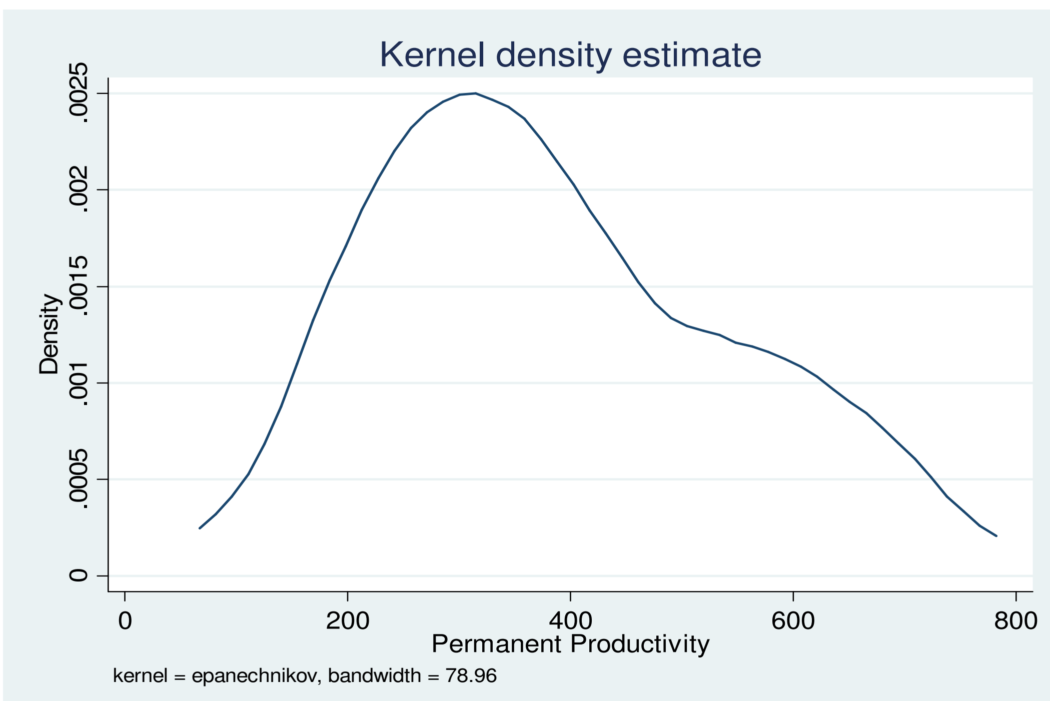
For robustness, we employ an additional test of the effect of worker heterogeneity on team performance. We first identify team sales for each three-hour period[11] in our data and, using the permanent productivities $\bar{y}'s$ estimated from our model, calculate each team's heterogeneity during that 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 permanent productivities of the best and worst current workers. Regressing total team sales on these

[11] This is because the combination of coworkers changes in every three-hour period due to the overlaps of the three shifts in a day.

heterogeneity measures and the control variables used in our peer effects 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 the model specification of our peer effects model.

Figure 3 shows the distribution of estimated worker permanent productivities, and Table 6 presents summary statistics of the average worker productivities for each brand, and compares these under the two compensation systems. Both are constructed from the asymmetric model results.[12] There is considerable variation in permanent worker productivity, and although the variation is much greater in some brands than others, this does not appear to be correlated with compensation systems. We note that the reported fixed effects are a mix of workers' own ability, brand quality as perceived by consumers, and the effect on work incentive from the two compensations. We cannot separately identify these three factors since brands do not change compensation system during our sample period, therefore, we must not interpret our findings as suggesting that TC counters are more productive than IC counters.

Figure 3: Distribution of Workers' Permanent Productivities



[12] Results from the symmetric model are very similar.

Table 6: Worker Permanent Productivity by Brand

Brand	Salesperson Permanent Productivity Mean	S.D.	Min	Max
Brand 1	558.70	116.37	331.38	703.27
Brand 2	439.50	158.93	289.77	703.00
Brand 3	548.53	57.99	466.67	602.38
Brand 4	308.58	44.80	274.71	372.08
Brand 5	185.07	32.33	145.94	222.44
Brand 6	292.50	40.60	232.72	323.25
Brand 7	476.98	49.95	411.30	555.66
Brand 8	274.68	22.56	257.30	306.02
Brand 9	286.53	81.82	159.46	381.65
Brand 10	305.16	19.23	293.65	327.36
Brand 11	291.56	8.93	279.25	300.29
IC Counters	385.04	139.00	159.46	703.27
TC Counters	387.39	166.48	145.94	703.00
Overall	385.96	149.06	145.94	703.27

5. Sales Strategies under Peer Effects

In the previous section we have demonstrated how the direction and magnitude of peer effects differ under the two compensation systems, and how these imply the impact of worker productivity diversity on team performance. Another important question we would like to address is: what strategies do salespeople adopt in response to the existence of peers under the two compensation systems which may explain our findings of peer effects? In this section, we first examine how coworker permanent productivity can influence other outcomes of a salesperson along several dimensions: unit sales, discounting, and number of customers served. We expect to find peer effects on unit sales and number of customers served similar to those on revenue sales. These results will test the robustness of our previous findings. Results of peer effects on discounting help us understand how salespeople may respond to star coworkers by offering heavy discounts, a strategy that may increase their sales but not necessarily benefit firms from a profitability perspective. In a set-up similar to the symmetric model in previous section, we run the following regression for salesperson *j* working for brand *i* on day *t*:

$$
\begin{aligned}
d_{ijt} = {} & \overline{d_j} + \left(\gamma_1^d \cdot 1\{i \in IC\} + \gamma_2^d \cdot 1\{i \in TC\}\right) \cdot \left\{ \sum_{k \in i; k \neq j} \left[\left(\sum_{h \in T_{kt} \cap T_{jt}} \frac{1}{N_{ih} - 1} \right) \cdot \left(\overline{y_k} - \overline{y_j}\right) \right] \right\} \\
& + \left(\gamma_3^d \cdot 1\{i \in IC\} + \gamma_4^d \cdot 1\{i \in TC\}\right) \cdot \left\{ \sum_{k' \in i'} \left[\left(\sum_{h \in T_{k't} \cap T_{jt}} \frac{1}{N_{i'h}} \right) \cdot \left(\overline{y_{k'}} - \overline{y_j}\right) \right] \right\} \\
& + \left(\gamma_5^d \cdot 1\{i \in IC\} + \gamma_6^d \cdot 1\{i \in TC\}\right) \cdot \left\{ \sum_{k'' \in i''} \left[\left(\sum_{h \in T_{k''t} \cap T_{jt}} \frac{1}{N_{i''h}} \right) \cdot \left(\overline{y_{k''}} - \overline{y_j}\right) \right] \right\} \\
& + \sum_{h \in T_{jt}} Z_h \beta + \tau_{ijt} \qquad (5)
\end{aligned}
$$

where the dependent variable d_{ijt} represents either (i) the total daily unit sales, (ii) the daily discounting percentage or, (iii) the total number of customers served in that day. The discounting percentage is defined as the ratio of the total amount of discounts offered to customers over the total dollar sales in a day. $\overline{d_j}$ is the fixed effect capturing individual's time-invariant unit sales, discounting, or customers served, due to her ability or intrinsic preferences, $\bar{y}$'s are the permanent productivities, and γ^d's represent peer effects on the dependent variables here.

Similar to the asymmetric model in previous section, we also examine how coworkers with higher and lower productivity can heterogeneously influence a salesperson's unit sales, discounting, and number of customers served. The only difference with equation (5) is that for each peer effect γ_g^d, where $g = 1, \ldots, 6$, we now estimate two separate effects $\gamma_g^{d,a}$ and $\gamma_g^{d,b}$ from coworkers with higher or lower permanent productivity. Altogether we have 12 γ^d's for each dependent variable.

In model estimation we use the estimated $\bar{y}$'s and indicators $\{\bar{y}_j \le \bar{y}_k\}$ and $\{\bar{y}_j > \bar{y}_k\}$, for every pair of coworkers *j* and *k*, from the previous sales revenue model. Since $\bar{y}$'s and indicators $\{\bar{y}_j \le \bar{y}_k\}$ and $\{\bar{y}_j > \bar{y}_k\}$ are treated as data, our symmetric and asymmetric models are both linear in γ^d's. OLS is used to estimate the models of unit sales and customers served. We use a one-sided Tobit model to estimate the price discounting model, as we frequently observe in the data no discounting being offered. Results estimated from the symmetric and asymmetric models are qualitatively very similar. To save space we only report the results using the asymmetric model in Table 7 (under columns 1 – 3).

Table 7: Peer Effects on Selling Strategies

			(1)	(2)	(3)	(4)	(5)
			Unit Sales	Discounting	Customers Served	High-Valued Customers	Low-Valued Customers
Within IC Counter	From Higher	$\gamma^{d,a}_{1}$	-.0013***	.0780***	-.0009***	-.0004***	-.0007***
			(.0002)	(.0243)	(.0001)	(.0001)	(.0000)
	From Lower	$\gamma^{d,b}_{1}$	.0005	.0107	-.0002	.0001	-.0003***
			(.0004)	(.0106)	(.0001)	(.0001)	(.0001)
Within TC Counter	From Higher	$\gamma^{d,a}_{2}$	.0024**	-.0005	.0008	.0005*	.0003
			(.0011)	(.0074)	(.0005)	(.0003)	(.0002)
	From Lower	$\gamma^{d,b}_{2}$	-.0003	.0025	-.0007**	-.0003*	-.0004***
			(.0006)	(.0142)	(.0003)	(.0002)	(.0001)
IC -> IC	From Higher	$\gamma^{d,a}_{3}$	-.0029***	.0431***	-.0015***	-.0007***	-.0008***
			(.0004)	(.0118)	(.0002)	(.0001)	(.0001)
	From Lower	$\gamma^{d,b}_{3}$	-.0025***	.0420***	-.0014***	-.0007***	-.0007***
			(-.0004)	(.0113)	(.0002)	(.0001)	(.0001)
IC -> TC	From Higher	$\gamma^{d,a}_{4}$	-.0021***	.0088*	-.0010***	-.0005***	-.0005***
			(.0004)	(.0049)	(.0002)	(.0001)	(.0001)
	From Lower	$\gamma^{d,b}_{4}$	-.0041***	.0188***	-.0022***	-.0010***	-.0012***
			(.0005)	(.0071)	(.0002)	(.0001)	(.0001)
TC -> IC	From Higher	$\gamma^{d,a}_{5}$	-.0079***	.0857***	-.0048***	-.0021***	-.0026***
			(.0009)	(.0240)	(.0004)	(.0002)	(.0002)
	From Lower	$\gamma^{d,b}_{5}$	-.0013**	.0347***	-.0010***	-.0007***	-.0002*
			(.0006)	(.0104)	(.0003)	(.0002)	(.0001)
TC -> TC	From Higher	$\gamma^{d,a}_{6}$	-.0027***	.0156	-.0015***	-.0008***	-.0008***
			(.0008)	(.0106)	(.0004)	(.0002)	(.0002)
	From Lower	$\gamma^{d,b}_{6}$	-.0022***	.0083	-.0012***	-.0007***	-.0005***
			(.0006)	(.0064)	(.0003)	(.0002)	(.0001)

The results illuminate the ways in which workers respond to peer effects. Increased competition from improved outside peer quality lowers unit sales and the number of customers served while increasing level of discounting. More importantly, the magnitude of these estimated parameters depends strongly on the compensation system of both the focal worker and her outside peer. Within IC counters, while superiors at the same counter hurt peer unit sales (-.001) and customers served (-.0009), inferiors have little effect. As a response, workers change their pricing strategy by offering discounts to potential customers. Column (2) shows that superiors increase the price discounting of their peers (.078) while inferiors have no effect. These results imply that worker heterogeneity in IC counters reduces revenue through reduced unit sales and increased price discounting among workers with lower productivity. Results of peer effects within TC counters tell a different story. While the existence of superior workers helps to increase unit sales (.002), the existence of inferior workers increases the number of customers a salesperson serves (-.007).[13] There is no discounting effect within TC counters. All these results suggest that worker heterogeneity in TC counters increases revenue through increased unit sales and customers served.

Cross-counter results also show a consistent story. High-ability workers at IC counters have little impact on TC counters ("IC -> TC"), causing very small decreases in unit sales (-.002) and a slight increase in discounting (.008). Conversely, TC counters gain from competing with low-ability IC workers in unit sales (-.004) and they are less likely to offer discounting (.019). The competitive peer effects of TC superiors on IC counters are stronger ("TC -> IC"). TC superiors greatly reduce IC unit sales (-.008) and in response IC workers dramatically increase discounting (.086). Yet IC counters gain very little from inferiors at TC competitors in terms of unit sales (-.001) that is considerably less than the loss to TC superiors. The resistance of TC counters to high-ability peers at competing counters is also evident in competition between TC counters ("TC -> TC"). While we observe similar asymmetric peer effects, these are smaller than those from TC counters to IC counters ("TC -> IC"). We also observe no peer effects between TC counters in discounting. Collectively, these cross-counter peer effects suggest that TC counters are better able to exploit weak workers at competing counters and defend themselves from competitors' star workers. This implies that coordination with team-based counters, perhaps through specialization, creates better dynamic responses to variations in worker-specific competition.

5.1 Peer Effects on Customer Mix

In response to the pressure from competing peers, a salesperson may employ strategies other than price discounting. For example, she may exert different levels of effort toward serving different types of customers. To investigate this possibility, we separate all the customers into two groups, using the median dollars spending as the separating criterion. We label them high-value (HV) customers and low-value (LV) customers. Columns (4) and (5) of Table 7 show the

[13] The effect of the existence of superior workers on customers served, though positive, is insignificant.

results when we estimate model (5) using the number of customers in these two groups as dependent variables.

Results again demonstrate negative peer effects within IC counters (γ^d_1), but the level of business stealing appears to be higher with LV customers (-.0007 vs. -.0004). Inferior coworkers appear only lose LV customers to superiors within counter (-.0003). More importantly, our results suggest some mechanisms through which worker heterogeneity might benefit TC counters. Superiors increase coworker sales more than inferiors increase coworker sales to HV customers (.0005 vs. -.0003), while only inferiors significantly increase coworker sales to LV customers (-.0004). This suggests that workers at TC counters may coordinate in which customers they serve: high-ability workers may let low-ability workers focus on selling to HV customers while they focus on competing with other counters for casual walkthrough traffic who are mainly LV customers. Since HV customers may purchase more units per transaction but may be less numerous than the LV customers in the store, this result helps to explain our previous findings that only high-ability workers help to increase unit sales for low-ability peers, and only low-ability workers significantly help to increase customers served for high-ability workers. Such a division of labor can be efficient if HV customers are brand-loyal and hence may purchase from the counter regardless of who the salesperson is. But walk-through customers must be competed for across counters, and assigning the best worker to this task may most efficiently utilize the skill-set of the workers.[14]

6. Discussion and Conclusion

In this paper we find evidence of peer effects among retail cosmetic salespeople. The peer effects are not simply productivity spillovers, as we also identify likely strategic responses by workers to the ability of their peers. The direction and magnitude of these effects depend on the compensation system used by the brand. When faced with high-ability peers within the counter, workers under individual-based compensation employ two strategic responses. First, they discount their prices offered to customers. Second, they focus on retaining high-value repeat customers, who likely are more loyal to specific brands. Still, they will lose (especially low-value) customers since they are unable to compete with high-ability peers in selling techniques.

[14] Interviews with the store management revealed that customer brand loyalty is very important for the cosmetics category. Once a customer is used to using a product, the cost of her switching to other products is very high. Therefore, the task of selling to a brand-loyal customer is much easier than attracting a new customer.

However, high-ability workers do not gain much overall. The reason is that workers at IC counters are less able to compete with outside peers especially from TC counters. Focusing on competing against each other, workers at IC counters can only devote limited effort to outside competition, and therefore are greatly impacted by high-ability outside peers. Our results demonstrate how the relationship between worker heterogeneity and team performance depends critically on compensation system – under individual-based compensation, heterogeneity can lead to internal customer and price competition, and loss of sales to outside competition.

In contrast, larger heterogeneity enhances team performance under team-based compensation. We find that high-ability workers significantly improve the sales productivity of their peers. Workers appear to coordinate on which customers they serve: low-ability workers may focus more on loyal high-value customers while high-ability workers compete for casual walkthrough customers who are most difficult to gain. Workers at these counters, finding it unnecessary to exert effort toward within-counter competition, can focus all effort toward outside competitors. Consequently, these workers lose fewer customers to outside peers and offer less discounting to customers, hence suffering less revenue loss. High-ability workers at TC counters, on the other hand, have much larger negative effects on outside peers than do their IC counter peers.

This paper is the first empirical study that simultaneously estimates peer effects within and across firms under multiple compensation systems. It is also the first to identify some strategies employed by workers in response to peer effects, and provides important implications for managerial decisions on staffing, compensation, and pricing discretion. Our results are consistent with existing theoretical models on incentives and employee helping behavior and task choice. We hope that our rich findings of peer effects in co-located sales teams will provide useful insights to stimulate future theoretical development, particularly in the context of cross-firm competition. Previous research suggests that productivity spillovers may occur from knowledge transfer, coordination and specialization, social pressure, and free-riding in teamwork. Empirical studies suggest that diversity will increase gains in a team. Yet these studies do not compare peer effects under different incentive schemes. We show that workers under individual-based compensation system respond to high ability peers by price discounting and strategically choosing customer types. Due to these behaviors, larger heterogeneity leads to lower team performance, especially when outside competition exists. We believe theoretically explicating how worker strategies under peer effects depend on compensation is important for future research. Furthermore, to our best knowledge, there has been no research in labor economics on how compensation system may influence the capability of a team or firm to compete against other teams or firms. Some of the existing theories on firm competition from the IO and strategy literature may be useful in addressing this issue. Our results on how peer effects spill across firm boundaries and instigate strategic responses from peers within and across firms may provide useful insights for future studies.

Finally, we note that there are several other issues in our analysis that should be addressed. First, we are unable to compare workers' overall productivity under individual-based and team-based compensation system. To achieve this would require counters to change their compensation systems in the data. Second, while we have identified the contemporary peer effects within and across counters, our model abstracts away from long-term peer effects that may be resulted from peer learning through team coordination or competition. A dynamic model allowing for peer learning can help to investigate this long-term effect. Addressing these two issues will allow us to finally study under what conditions it will be optimal for firms in a competition environment to adopt individual-based vs. team-based compensation system.

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