Peer Bargaining and Productivity in Teams: Gender and the Inequitable Division of Pay

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This paper shows that when teams are allowed to internally allocate rewards, the ensuing peer bargaining process generates inequitable outcomes toward women based both in social processes and distributional preferences. We use risk-adjusted fixed-effect models to identify productivity and peer bargaining traits in 965 workers at 32 large Chinese beauty salons. We identify individual productivity through service and card sales and bargaining through the division of team-based commissions. Although productivity and peer bargaining outcomes are positively correlated, a substantial number of workers have bargaining traits that do not match their productivity. More importantly, we show that women consistently receive bargaining outcomes below their productivity level, while men are consistently overcompensated, and confirm this disparity using Extreme Gradient Boosted Trees machine learning models. Finally, we build a theoretical model to derive a numerical method of moments solution that shows our results can only be explained by a combination of higher prosociality and lower bargaining power in women.

Key words: Productivity, Bargaining, Gender, Negotiation, Equity, Fairness, Compensation

1. Introduction

Team-based production is essential to modern firms (Coff 1997, Moreland and Argote 2003, Wuchty et al. 2007), yet managers face the constant challenge of allocating tasks and rewards to team members when individual ability, effort, and performance are hard to measure (Prendergast 1999). To counter this information problem, managers often rely on team members to allocate tasks (Barron and Gjerde 1997, Jung et al. 2017) and assign credit and rewards (Shaw et al. 2001, Bamberger and Levi 2009) among their peers. Ideally, peers would efficiently allocate tasks based on relative productivity advantages and equitably assign rewards based on contributions. As recent

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work shows, however, this is frequently not the case. Women, for example, often receive the less-desirable tasks (Babcock et al. 2017), inequitably low pay (Bowles and McGinn 2008, Castilla 2008), and insufficient recognition (Sarsons 2017). We represent this often-inequitable peer-based allocation of tasks and rewards as “peer bargaining”, where tasks and earnings are negotiated among coworkers. We argue that peer bargaining, like productivity (Huckman and Pisano 2006, Hamilton et al. 2003, Mas and Moretti 2009), represents a persistent individual trait based in distributional preferences and social structure that may be only loosely coupled with worker output.

We empirically identify individual productivity and peer bargaining traits by exploiting a unique setting of 1,295 workers in 32 large beauty salons in Beijing, China. Workers in small teams receive fixed individual commissions for services (e.g., hair, cosmetics) and team-based commissions for pre-paid card sales. Services and card sales allow us to identify two productivity measures for each worker. The team commission, which is divided at the discretion of team members, provides a separate measure of worker bargaining outcomes. This combination of individual productivity and bargaining measures thereby address our primary research question—how frequently are persistent worker bargaining outcomes misaligned with true productivity, and why does this misalignment exist?

We use simultaneous fixed effect models to separately identify each worker’s peer bargaining trait and two classes of permanent productivity: service revenue and card sale revenue. Individual worker productivity is measured as worker fixed effects when controlling for transaction characteristics based on time, task, and coworkers (e.g., Huckman and Pisano 2006, Mas and Moretti 2009). Peer bargaining traits are similarly measured through worker fixed effects in regressions predicting commission share in two-person card sales.

We find strong evidence of heterogeneity in workers’ unique productivity and peer bargaining traits. Although worker productivity is positively correlated with peer bargaining, a substantial number of workers are either over- or under-compensated through peer bargaining. Many workers consistently receive high commission shares despite their low productivity, while others receive low bargaining outcomes that do not reflect their high output. Most strikingly, we find that gender strongly predicts under- or over-compensation relative to productivity. Although male and female workers have indistinguishable productivity distributions, men have much higher peer bargaining outcomes. Men make up a disproportionate number of highly compensated yet unproductive workers, while women over-represent stars with poor bargaining outcomes.

We argue that the peer bargaining trait can result from two broad sources known to differ between men and women. First, a worker may accept less advantageous bargaining outcomes because of distributional preferences for fairness or equity (Huseman et al. 1987, Rabin 1993, Fehr and Schmidt 1999)—preferences more commonly found in women than in men (Croson and Gneezy
2009). Prosocial preferences (Brief and Motowidlo 1986, Batson 1991, Frey and Meier 2004) may even motivate workers to accept shares that are below equity. Such workers have been described as “givers” (Grant 2013) or “mavens” (Oettl 2012).

Second, peer bargaining traits reflect the worker’s bargaining power vis-à-vis her team members, which includes two main factors. First, it reflects inherent bargaining ability, or the skill in achieving advantageous divisions of value (Raiffa 1982, Malhotra and Bazerman 2008b). Both economists and psychologists argue that a substantial proportion of bargaining outcomes are based on ability or skill (Elfenbein 2015) that may be inherent or learned (Nadler et al. 2003). Second, bargaining power is also based on how the embedded social dynamics of ethnicity (Tinsley and Pillutla 1998), status (Blader and Chen 2011), and gender (Bowles and McGinn 2008, Babcock et al. 2017, Bowles et al. 2007). Studies consistently find women to have weaker bargaining power in both laboratory and field settings.

Our paper contributes to several important research streams. First, we provide unique evidence that the division of value within the firm is heavily embedded in gender-based social dynamics (Bowles and McGinn 2008, Babcock and Laschever 2009, Castilla 2008). Consistent with recent work (Babcock et al. 2017, Sarsons 2017), we find that discretionary bargaining among workers leads to consistent inequity toward women. Female workers in our setting receive much less pay than their male counterparts despite indistinguishable productivity. Importantly, we can also show that both equity preferences and social structure contribute to this pay gap. Our work is consistent with the gender equity literature (Blau and Kahn 2007, Bidwell et al. 2013, Fernandez-Mateo 2009, Cook et al. 2018, Castilla 2015) and with Chatman’s argument that the dynamics of mixed-sex work groups are embedded in social and cultural norms that are crucial to team performance (Chatman 2010). To the best of our knowledge, ours is the first paper to show that the discretionary division of compensation among peers generates gender inequity in an organizational setting.

Second, we add to the literature on star employees (Aguinis and O’Boyle 2014, Groysberg and Lee 2009) and their influence on peers. Most of this literature studies how high productivity workers increase peer performance through social pressure (Mas and Moretti 2009), helping (Chan et al. 2014a), knowledge transfer (Azoulay et al. 2010, Chan et al. 2014b, Castilla 2005) and recruiting better talent (Fernandez et al. 2000, Agrawal et al. 2017). Our paper builds on recent work that categorizes worker value on dimensions beyond task productivity. Oettl (2012) and Grant (2013) define and measure the value of employees not only on their own output, but also on their helpfulness toward peers. Burbano (2016) identifies worker preferences for social responsibility. Pierce and Snyder (2008) measure worker propensity for dishonesty. These studies collectively show that star employees cannot be defined purely on the direct and indirect impart of standard productivity measures.
We also expand on work in the strategic human capital literature (Coff 1997, Chadwick 2017, Lepak and Snell 1999, Campbell et al. 2012, Lee et al. 2015) by measuring the division of value among workers. Prior work has almost exclusively focused on value division between the firm and workers. To the best of our knowledge, we provide the first evidence on value division within team-based production in firms. Our evidence shows that the unique value captured from a specific employee includes how they bargain and interact with peers.

Finally, we provide a new application of machine learning in the management and organizations literature, using Extreme Boosted Gradient trees to validate the predictive value of worker characteristics for productivity and bargaining outcomes (Liaw and Wiener 2002). Such machine learning techniques have been used in business applications in other fields, such as Operations Management (Cui et al. 2017) This application answers the call for increased “big data” analytical techniques in the field of management (George et al. 2016).

2. Productivity and Peer Bargaining: Literature and Theory

A growing literature argues that employee productivity and prosociality are independent traits that jointly determine worker value in organizations with team-based production (Oettl 2012, Grant 2013, Cain et al. 2014). In this section, we discuss the two worker traits: productivity and peer bargaining. This second trait—peer bargaining—reflects two factors that jointly determine bargaining outcomes. The first factor, distributional preferences, influences bargaining outcomes through prosocial preferences for fair or equitable outcomes. The second factor, bargaining power, reflects both bargaining ability and the social dynamics that influence treatment by coworkers.

2.1. Worker Productivity Traits in Teams

Attracting and retaining the best talent has long been acknowledged as a critical component of firm performance (Rosen 1981, Schneider 1987). Individual differences in both ability and motivation yield large variation in worker output across a wide variety of job tasks and industry sectors, and can yield superior profitability for managers that can capture the value they generate (Campbell et al. 2012). Similarly, personnel economists increasingly argue that the greatest value of pay-for-performance systems is attracting top talent when ability is unobservable (Oyer et al. 2011, Lazear and Oyer 2012).

Attracting and retaining top talent is particularly important in teams, where the most productive workers can have positive spillovers to coworkers. These contemporaneous “peer effects” are widely documented across industries and tasks (Herbst and Mas 2015), including research scientists (Azoulay et al. 2010), salespeople (Chan et al. 2014a), and supermarket checkers (Mas and Moretti 2009).
Furthermore, high productivity workers might bestow permanent productivity increases to coworkers through peer learning processes. Scholars have long inferred peer-based learning by correlating either network structure (Ingram and Roberts 2000, Reagans and McEvily 2003) or team tenure (Edmondson et al. 2001, Huckman et al. 2009) with performance. More recent work has directly demonstrated how workers can impart long-term productivity gains on peers (Castilla 2005, Chan et al. 2014b, Kc et al. 2013, Bartel et al. 2014, Song et al. 2017).

Collectively, this research emphasizes that individual productivity is a crucial and heterogeneous trait in team-based production, but these typically focus on one dimension of productivity, with any group-based spillovers stemming directly from this trait.

2.2. Peer Bargaining

Recent work (e.g., Oettl 2012) has highlighted that traditional productivity traits fail to capture other individual differences that contribute to both team and organizational performance. We argue that peer bargaining, or the share of rewards and tasks allocated within teams, represents an important and persistent trait that varies across workers. In the team-based production systems common in firms, non-managerial workers are frequently given authority to collectively assign tasks and mete out rewards. Although task assignment within teams may be straightforward if based on obvious heterogeneous skill differences (Gibbons and Waldman 2004), it may also require bargaining if some tasks are more desirable than others. Some tasks may require more effort, or may be intrinsically less rewarding (Deci et al. 1999, Grant 2008) or even odious (Ashforth and Kreiner 1999). Coworkers may therefore have strong preferences over task allocation, forcing them to bargain over how the most and least desirable tasks are allocated. Workers in teams may also bargain over rewards. Rewards may be financial, such as through the negotiated division of team-based bonuses or commissions. Yet rewards may also be based on non-monetary credit for team performance. Individual contributions to team production may be opaque to managers or others outside the team, and they may rely on team members to help assess employee performance or potential for promotion, retention, or compensation. How individual team members take credit for group performance is also inherently a peer bargaining process, with potentially inequitable outcomes.

Persistent worker differences in the allocation of tasks and rewards within teams represent a peer bargaining trait that stems from multiple factors. Crucially, peer bargaining outcomes may not be purely explained by the productivity trait discussed above, where task and reward allocation is simply a function of contribution or ability. Instead, productivity and peer bargaining traits may be inequitably decoupled, where those who contribute the most are not rewarded the most. But as we explain next, since peer bargaining traits result not only from bargaining power but also from
distributional preferences, this inequity is not necessarily undesirable to workers. Consequently, it is crucial to understand through which mechanisms peer bargaining traits is determined: bargaining power that include bargaining ability and social factors, or workers’ distributional preferences.

2.2.1. Distributional preferences Humans have strong yet heterogeneous preferences for both fair (Huseman et al. 1987, Fehr and Fischbacher 2003, Kohlberg 1969, Fehr and Schmidt 1999, Haidt and Graham 2007) and prosocial (Brief and Motowidlo 1986, Frey and Meier 2004) outcomes. People on average care about fairness even when they are the beneficiary of inequitable outcomes (Loewenstein et al. 1989, Gino and Pierce 2010a), but the relative importance of fairness to own rewards varies considerably across individuals based on culture, beliefs, and demographics (Henrich et al. 2005, Graham et al. 2009, Andreoni and Vesterlund 2001).

Similarly, scholars have argued that prosocial helping behavior is a heterogeneous worker trait. For example, Oettl (2012) highlight that helpfulness is a unique trait in research scientists that is not perfectly predicted by individual productivity. Many scientists with modest individual research output generate great value by helping facilitate others’ productivity, while some “star” scientists are overvalued because their individual out represents their sole contribution. Grant’s (2013) definition of workers along the helping dimension provides similar conclusions. Cain et al. (2014) note, however, that empirical observations of prosociality can reflect a multitude of motivations and psychological processes. Workers who appear to be prosocial “givers” or “helpers” may indeed have prosocial preferences, but such traits may also reflect what they term “giving in”—prosociality based on the perceived inability to say no due to their bargaining power.

2.2.2. Bargaining power Although distributional preferences may define a worker’s preferred bargaining outcome, her ability to achieve that ideal point ultimately depends on her bargaining power—her ability to influence the outcome (Schelling 1956). Bargaining power is partly based on ability, which multiple research streams argue is heterogeneous and affects the division of value (Kray and Haselhuhn 2007, Bennett 2013, Grennan 2014, Elfenbein 2015). Work by Elfenbein et al. (2008), for example, found that individual differences explained over half of bargaining performance. Although individuals may possess permanent differences in bargaining ability due to cognitive capabilities (Malhotra and Bazerman 2008a), this ability may be developed by learning negotiation and influence skills (Nadler et al. 2003, O’connor et al. 2005).

The second determinant of bargaining power is a worker’s expected outside option. Although in an employment setting, this outside option might be partly determined by her redeployable human capital (Coff 1999), it also depends on how social structure shapes the interpersonal dynamics of bargaining. Peer bargaining, like all economic transactions, is embedded in social structure and dynamics (Granovetter 1985), and a worker’s characteristics can shape how her peers engage with
and respond to her in the bargaining process, and consequently how she will behave in anticipation of this response. Some workers, for example, may consistently inspire prosocial bargaining from others, while other workers might be treated aggressively or selfishly.

2.3. Peer Bargaining and Gender
Substantial evidence across disciplines shows that women consistently fare worse in bargaining or negotiation around salary and other outcomes (Bielby and Baron 1986, Kray and Thompson 2004, Stuhlmacher and Walters 1999, Mazei et al. 2015). Evidence of this gap comes not only from laboratory experiments, but also from organizations. Card et al. (2012), for example, use data from Portugal and find women have only 90% the bargaining power of their male coworkers in setting wages. Leibbrandt and List (2014) find this difference only exists when wage negotiation is not explicitly specified. Castilla (2008) finds consistently lower salary growth for women even under equivalent performance evaluations.

Although few field studies examine bargaining with peers, evidence on gender-based differences in both distributional preferences and bargaining power suggests that women fare poorly there as well. There is substantial evidence that women have stronger preferences for prosociality and equality. A meta-analysis of negotiation competitiveness from social psychology, for example, found women to be more cooperative in negotiations (Walters et al. 1998). Similarly, Croson and Gneezy (2009) review evidence in economics that women have stronger preferences for equality. Both Eckel and Grossman (2001) and Solnick (2001) also find that women are far more likely to reject an unequal ultimatum game proposal offered by a female partner than one from a man. Andreoni and Vesterlund (2001) found that when altruism is expensive, as in our setting, women are more altruistic in dictator games.

Past work also shows that women typically have less bargaining power than their male counterparts for systemic social reasons. Many argue that men are more competitive in negotiation (Walters et al. 1998) and more willing to cross ethical lines in doing so (Lee et al. 2017) because the returns to such behavior are higher. Social role theory argues that women receive financial or social backlash and opposition when negotiating aggressively (Eagly and Wood 2011, Tinsley et al. 2009, Amanatullah and Tinsley 2013), which may explain why women are less likely to initiate negotiations (Small et al. 2007, Babcock and Laschever 2009, Bowles et al. 2007). Related work shows the power of these social roles in marriage, where because men frequently are threatened by bread-winning wives, women may intentionally restrict their own earnings (Pierce et al. 2013, Tinsley et al. 2015).

The vast majority of this literature focuses on wages, but it may also apply to other types of rewards as well as task allocation. Heilman and Haynes (2005), for example, found that outside
observers attributed more of the credit for team performance to male members than to females. Sarsons (2017) finds that female academic economists are disproportionately punished in tenure promotions for coauthorship, largely because of the ambiguity of author order. Babcock et al. (2017) demonstrate that women are more frequently assigned those tasks that help little in career promotion, while Uribe and Carnahan (2018) find evidence of social loafing by men in mixed-gender teams that may reflect task responsibility.

2.4. A Formal Model of Peer Bargaining

We formally model how distributional preferences and bargaining power can generate peer bargaining outcomes using a one-shot Ultimatum Game with inequality aversion (Fehr and Schmidt 1999).

Following Fehr and Schmidt (1999), we assume that the bargaining game has a proposer and a responder, and without loss of generosity, that they split 1 unit of wealth. The bargaining game is as follows: The proposer proposes a share $s$ to the responder. If the responder accepts the proposal, she receives $s$, while the proposer receives $1-s$. If the responder declines the proposal, she receives her outside option $r_r$ and the proposer receives her own outside option $r_s$. In our context, this means that two workers have rational expectations over what splits they will receive if they team up to sell a card. If the expected value of teaming up is lower than the outside options for either worker, they will not form a team in the first place. Otherwise, they will form a team, generate the card sales, and split the commission based on the expected agreeable split.

Following Fehr and Schmidt (1999), we assume that workers may have distributional preferences, such that they care about outcomes that are inequitable to both themselves and their partners. The worker $i$’s utility for a split $(x_i, x_j$ such that $x_i + x_j = 1)$ is:

$$u_i(x_i, x_j) = x_i - \alpha_i \max\{x_j - x_i, 0\} - \beta_i \max\{x_i - x_j, 0\},$$

(1)

where $\alpha_i$ and $\beta_i$ represent the prosociality of the worker $i$. Similar to past work, we assume that $\beta_i < \alpha_i$, such that workers care more about disadvantageous inequity. Moreover, we assume that $\beta_i \leq 1$, or that no one is “absolutely” prosocial—the utility gained from getting 0.1 share of the pie is lower than the disutility from having a 0.1 difference in the bargaining outcomes. Last, we assume that $\max\{r_r, r_s\} \leq 0.5$, representing that an agent, regardless of whether she is the proposer or the responder, would have a positive chance of gaining utility while bargaining.

With this utility function, our bargaining game can be described by the primitives on the proposer’s and responder’s preferences and outside options $\theta = (\alpha_s, \alpha_r, \beta_s, \beta_r, r_r, r_s)$. Given the primitives, we can characterize the bargaining outcomes:
Proposition 1. Given the primitives of the bargaining game, \( \theta = (\alpha_s, \alpha_r, \beta_s, \beta_r, r_r, r_s) \), the bargaining outcome is:

\[
(x_s, x_r) = \begin{cases} 
(0.5, 0.5), & \text{if } \beta_s \geq 0.5 \text{ and } \beta_r < 0.5 \\
(r_s, r_r) & \text{if } \beta_s \geq 0.5 \text{ and } \beta_r \geq 0.5 \\
\left( \frac{1 + \alpha_r - r_r}{1 + 2 \alpha_r}, \frac{r_r + \alpha_r}{1 + 2 \alpha_r} \right) & \text{if } \beta_s < 0.5
\end{cases}
\]

where \((x_s, x_r)\) is the share that the proposer and responder receive and \(x_s + x_r = 1\) if there is a trade.

Proposition 1 (see Appendix for proof) shows that a worker’s final split is co-determined by her distributional preference and outside option. If a person has a higher prosocial preference, she will have higher \( \beta \) in the model. Moreover, the person’s outside option and his probability of being the proposer jointly determines her bargaining power. Therefore, a person will get higher average bargaining outcome if (a) she is more likely to be a proposer (\( p_i \) is larger), (b) she is less prosocial (\( \beta_i \) is smaller), (c) she dislikes having the smaller share (\( \alpha_i \) is larger), and (d) she has a higher outside option (\( r \) is larger).

Suppose that a worker \( i \) with \((\alpha_i, \beta_i, r_i)\) is bargaining with a pool of workers with primitives drawn from three distributions (\( \alpha \in A, \beta \in B \) and \( r \in R \)). The probability that worker \( i \) is a proposer is denoted as \( p_i \in (0, 1) \). The average split of worker \( i \) when there is a trade is denoted as \( x_i \). The following lemma (see Appendix for proof) formally summarizes the aforementioned comparative statics results related to average bargaining outcomes:

Lemma 1. \( x_i \) is weakly increasing in \( p_i \) and \( r_i \). \( x_i \) is weakly increasing in \( \alpha_i \) and \( x_i \) is weakly decreasing in \( \beta_i \).

Given Proposition 1, we can simulate a person’s share given his or her primitives. In particular, we assume that the worker bargains with a population of workers whose \( \alpha \) is drawn from a uniform distribution on \([0, 1]\), and \( \beta \) is drawn from a uniform distribution on \([0, \alpha]\), and \( r \) is drawn from a uniform distribution on \([0, 0.5]\). We simulate the worker’s average bargaining outcomes with respect to \( r_i \in [0, 0.5] \) and \( x_i \in (0, 1) \), \( \alpha_i = 1.0 \) and \( \beta_i \in \{0.25, 0.75\} \).

Panel A in Figure 1 represents the average payoff of the agent with respect to her outside option and proposing probability under low prosociality (\( \beta = 0.25 \)). As the agent’s bargaining power increases—her outside option (\( r_i \)) or proposing probability (\( p_i \)) increases—the agent has a higher average payoff regardless of \( \alpha_i \) and \( \beta_i \). Panel B of Figure 1 shows the average payoff under high prosociality (\( \beta = 0.75 \)). Again, as the agent’s bargaining power increases, the agent has a higher average payoff regardless of \( \alpha_i \) and \( \beta_i \). Moreover, comparing the two panels, we find that the agent will receive lower payoff (for each pair of \( x_i \) and \( r_i \)) if the agent has a higher \( \beta \).

Our model implies that there are multiple reasons why a worker might have a lower peer bargaining trait. First, she may have a stronger fairness preference \( \beta \). Second, she may have a lower
outside option $r$. Third, she may have a lower probability of being the proposer, which in our case can represent bargaining ability.

3. Empirical Setting

We estimate the joint distribution of worker productivity and peer bargaining in a service industry setting, using 50 months of earnings and productivity data from 1,295 workers at 32 large salons in Beijing, China. This setting has several unique characteristics that make it ideally configured for identifying joint heterogeneity in worker productivity and peer bargaining. First, workers engage in two important task types for the firm. Although their primary task is to provide services such as nails, hair, or massage, they also sell prepaid cards that can be used for later services. Our dataset contains 1,387,979 total transactions, of which approximately 5.9% are card sales.

Nearly all customers are engaged by teams of multiple workers providing one or more specific services. Most importantly for our research question, the two task types are compensated differently. Each specific service has a fixed individual commission paid to the worker that is beyond their control (typically 21%). In contrast, prepaid cards that are sold by teams produce a 9% team-based commission that workers bargain over to divide among themselves. In this way, we can observe the productivity on one task type where value division is fixed, and another where it is discretionary. We also benefit from strong norms against tipping in China, which ensures that we observe total compensation for each worker.

Table D.2 presents summary statistics for our 67,525 two-person card transactions, 1,577,954 service transactions, and 965 workers with at least 10 weeks of data (see Appendix for summary...
Table 1 Summary Statistics of All Transactions and Workers

<table>
<thead>
<tr>
<th>Variable</th>
<th>No. of Obs</th>
<th>Mean</th>
<th>Std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Two-employee Card Transactions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue</td>
<td>67,525</td>
<td>2,473.897</td>
<td>3,093.813</td>
<td>8.0</td>
<td>49,000</td>
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<tr>
<td>Commission</td>
<td>67,525</td>
<td>101.421</td>
<td>149.9</td>
<td>0.0</td>
<td>3,969</td>
</tr>
<tr>
<td>Commission Cut</td>
<td>67,525</td>
<td>0.505</td>
<td>0.243</td>
<td>0</td>
<td>1.000</td>
</tr>
<tr>
<td>Hour</td>
<td>67,525</td>
<td>16.897</td>
<td>3.709</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td>Weekend</td>
<td>67,525</td>
<td>0.374</td>
<td>0.484</td>
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<td>1</td>
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<tr>
<td>Month</td>
<td>67,525</td>
<td>6.461</td>
<td>3.566</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>Year</td>
<td>67,525</td>
<td>2011.7</td>
<td>0.916</td>
<td>2009</td>
<td>2013</td>
</tr>
<tr>
<td>New Card</td>
<td>67,525</td>
<td>0.502</td>
<td>0.500</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Panel B: Service Transactions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of Workers</td>
<td>1,577,954</td>
<td>1.814</td>
<td>1.271</td>
<td>1</td>
<td>22</td>
</tr>
<tr>
<td>Revenue</td>
<td>1,577,954</td>
<td>138.600</td>
<td>252.7</td>
<td>5.2</td>
<td>4,995</td>
</tr>
<tr>
<td>Commission</td>
<td>1,577,954</td>
<td>23.939</td>
<td>42.684</td>
<td>0.0</td>
<td>3,510</td>
</tr>
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<td>Hour</td>
<td>1,577,954</td>
<td>17.248</td>
<td>3.562</td>
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<td>23</td>
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<td>Weekend</td>
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<td>0.354</td>
<td>0.478</td>
<td>0</td>
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</tr>
<tr>
<td>Month</td>
<td>1,577,954</td>
<td>6.299</td>
<td>3.539</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>Year</td>
<td>1,577,954</td>
<td>2011.6</td>
<td>1.013</td>
<td>2009</td>
<td>2013</td>
</tr>
<tr>
<td>Appointment</td>
<td>1,577,954</td>
<td>0.128</td>
<td>0.335</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Junior Worker</td>
<td>1,577,954</td>
<td>0.204</td>
<td>0.403</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Senior Worker</td>
<td>1,577,954</td>
<td>0.593</td>
<td>0.491</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Intern Worker</td>
<td>1,577,954</td>
<td>0.073</td>
<td>0.260</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Beautician</td>
<td>1,577,954</td>
<td>0.118</td>
<td>0.323</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Product Sale</td>
<td>1,577,954</td>
<td>0.012</td>
<td>0.109</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Panel C: Worker Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>965</td>
<td>28.59</td>
<td>4.94</td>
<td>19</td>
<td>47</td>
</tr>
<tr>
<td>Start Year</td>
<td>965</td>
<td>2010.6</td>
<td>1.07</td>
<td>2009</td>
<td>2013</td>
</tr>
<tr>
<td>Male</td>
<td>965</td>
<td>0.52</td>
<td>0.5</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>High School Education</td>
<td>965</td>
<td>0.26</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: The table contains all observations related to the 965 workers who have at least worked 10 weeks in our sample period. The unit of observation is employee-transaction. Therefore, for each transaction in Panel A and Panel B, there may be multiple observations, depending on whether this transaction is completed by multiple employees. All currency is in Chinese Yuan (CNY).

statistics by gender). The average service costs 139CNY (about 22USD), while the average prepaid card sale is 2,474CNY (396USD).

4. Identification Strategy

We empirically identify productivity and peer bargaining traits as worker fixed effects in linear regressions that control for transaction/service type, schedule shifts, flexible time trends, salon location, and coworkers. This approach, often referred to as “risk adjustment”, is widely used to estimate employee or facility performance in industries such as health care (Huckman and Pisano 2006), food service (Mas and Moretti 2009), automotive service (Pierce and Snyder 2008), and sales (Chan et al. 2014a). The approach estimates an employee’s average performance, conditional on the unique mix of positive and negative conditions that they face. For the heart surgeons in Huckman and Pisano (2006), for example, a surgeon’s performance measure is adjusted to account for risk factors such as pre-existing conditions, age, and gender. For the team-based settings in
Mas and Moretti (2009) and Chan et al. (2014a), the model also controls for shift-specific customer traffic and the mix of coworkers.

We estimate three separate regressions: two predicting weekly revenue generation and one predicting transaction commission split. The two revenue regressions, which are used to estimate permanent productivity, separately use weekly service revenue and weekly card sales revenue as dependent variables. The commission regression, which estimates the peer bargaining trait, uses only those transactions with teams of two workers (87% of all card sales) to regress each worker’s commission share on worker fixed effects and control variables. We detail each regression below.

4.1. Estimating Worker Service Productivity

We use the following equation to estimate each worker’s permanent productivity in generating service revenue:

\[
\log(\text{Service Revenue}_{it}) = G_s + \text{Transaction Type}_{it} + \text{Week}_t + \text{Worker Type}_{it} + \text{Shift}_{it} + \text{Store}_i + \epsilon_{it}.
\]

(2)

The unit of analysis is the worker-week. The dependent variable is the average logged daily revenue for worker \(i\) at his salon \(i\) in week \(t\) based on the actual number of days worked in week \(t\). For each service, we observe the list of workers who have contributed to this service. Therefore, for services performed in teams, we allocate revenue equally to individual employees who participated in the service.

We also include controls that might influence a worker’s weekly service productivity. Since we focus on all non-card transactions, some of which involve 10 workers, we control for the average number of coworkers in worker \(i\)’s teams during week \(t\). We control for the weekly percentage from tasks of seven types. The six most commonly coded tasks involve more than 64% of all transactions: “beautification”, “style”, “stylist haircut”, “massage”, “simple haircut”, and “hair care”. The remaining 36% include over 1,000 rare task descriptions that we collectively code as “other”. We also control for the level of workers, which include “interim worker”, “junior worker”, “senior worker”, and “beautician”. Store dummies address store-level sales differences. We control for the 14 shift assignments (morning and evening) in a week with dummies and include week fixed effects. The variables of interest are the individual fixed effects in vector \(G_s\), which represent the risk-adjusted permanent service productivity for all workers.

\(^1\) In our sample, all workers have only one salon at any given week, therefore, we use the individual subscript to represent the salon fixed effect.
4.2. Estimating Worker Card Sales Productivity

We also estimate a worker’s productivity in selling prepaid cards using the following regression model:

\[ \text{Log}(\text{Card Revenue}_{it}) = G^c_i + \text{Card Initiation}_{it} + \text{WorkerType}_{it} + \text{Week}_t + \text{Shifts}_{it} + \text{Store}_i + \epsilon_{it}. \]  (3)

The dependent variable is the log of total weekly revenue generated by worker \( i \) at salon \( j \) in week \( t \) through card sales. In this analysis, we limit our sample to only those transactions with teams of two workers (87% of total card transactions) to be consistent with our bargaining estimation sample below. Card Initiation details the percentage of card sales that are refills. Also included are week and shift fixed effects. The variables of interest are the individual fixed effects in vector \( G^c \), which represent the risk-adjusted permanent sales productivity for all workers.

4.3. Estimating Worker Peer Bargaining Trait

We use the following equation to estimate each worker’s bargaining trait as an individual fixed effect:

\[ \text{Cut}_{ijt} = C^c_i + \text{Coworker}_j + \text{TotalCommission}_{ijt} + \text{TransactionType}_{ijt} + \text{CumulativeNumTransactions}_{it-1} + \text{Week}_t + \text{Store}_i + \text{Shift}_t + \epsilon_{ijkt}. \]  (4)

We limit our peer bargaining sample to only those transactions with teams of two workers, and define the dependent variable \( \text{Cut}_{ijt} \) as the percentage of total commission received by worker \( i \) working with coworker \( j \) on transaction \( ijt \). Our unit of analysis is an individual transaction. Unlike in the productivity regressions, we do not aggregate to weekly levels because we wish to control for the identity of coworkers in a particular transaction. We intentionally control for the cumulative number of card transactions before the transaction as a good approximation of their ability in generating card sales. By controlling for this, the estimated worker bargaining trait should not be confounded by her sales productivity. Again, we control for the store, week, shift and type of transaction (i.e., card sales v.s. card refill) fixed effects.

5. Results
5.1. Bargaining and Productivity Estimates

We estimate models 2-4 using ordinary least square (OLS) with standard errors clustered at the worker level, identifying productivity traits \( G^p \) and \( G^c \) and bargaining trait \( C^c \) for the 627 workers with at least 30 card transactions and 30 weeks of service. We define the four quadrants in Figure D.4 by summing the two productivity fixed effects estimated in equations 2 and 3 to generate \( G^p_i \)—the total productivity trait for worker \( i \). We define each quadrant by median fixed effect on both the productivity and peer bargaining dimensions.
Figure 2 presents the joint distribution of productivity and peer bargaining fixed effects for the 627 workers with at least 30 card transactions. Vertical and horizontal lines represent the median worker on productivity and peer bargaining, respectively. Worker productivity fixed effects in our service productivity model explain 20% of all variance, while worker fixed effects in our card sales productivity model explain 8% of variance. Worker fixed effects in our peer bargaining models explain 40% of the variance. Collectively these results show that individual traits on both productivity and peer bargaining dimensions are important predictors of outcomes.

Furthermore, Figure 2 shows that although peer bargaining traits are indeed correlated with task productivity ($\beta=0.277$, SE=.036), there is enough covariance to suggest that peer bargaining is individual trait. To aid exposition, we divide workers into four groups by median productivity and bargaining (see Table 2 in the Appendix). We designate workers with both above-median productivity and peer bargaining traits as “Equitable Stars”, while “Equitable Laggards” are those with both low productivity and peer bargaining. Each of these two groups on average receive peer bargaining outcomes consistent with their productivity. “Net Contributors” are those with above-median productivity but below-median peer bargaining. The low value they receive in peer bargaining does not reflect their high productivity contribution to the firm. In contrast, “Net Extractors” have low productivity yet still receive above-median peer bargaining outcomes.

Both Figure 2 and Table 2 show that although the majority of workers are in the “equitable” quadrants, a significant portion (39%) are off-diagonal. An alternative sample, where we loosen sample restrictions to include the 965 workers with at least 10 card transactions and 10 months
Table 2: Worker Categorization by Productivity and Bargaining Estimates

<table>
<thead>
<tr>
<th>Worker Type</th>
<th>Productivity ((G_i))</th>
<th>Bargaining ((C_i))</th>
<th>Sample A Total</th>
<th>Sample B Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Contributor</td>
<td>High</td>
<td>Low</td>
<td>123</td>
<td>198</td>
</tr>
<tr>
<td>Equitable Stars</td>
<td>High</td>
<td>High</td>
<td>190</td>
<td>284</td>
</tr>
<tr>
<td>Equitable Laggards</td>
<td>Low</td>
<td>Low</td>
<td>191</td>
<td>285</td>
</tr>
<tr>
<td>Net Extractors</td>
<td>Low</td>
<td>High</td>
<td>123</td>
<td>198</td>
</tr>
<tr>
<td><strong>Total Workers</strong></td>
<td></td>
<td></td>
<td><strong>627</strong></td>
<td><strong>965</strong></td>
</tr>
</tbody>
</table>

Note: This table shows the number of workers who fall in each of four quadrants defined by median productivity and bargaining. Sample A requires a minimum of 30 weeks service, while Sample B requires 10 weeks.

Table 3: Worker Categorization by Gender

<table>
<thead>
<tr>
<th>Worker Type</th>
<th>Productivity ((G_i))</th>
<th>Bargaining ((C_i))</th>
<th>Sample A Men</th>
<th>Sample A Women</th>
<th>P-value</th>
<th>Sample B Men</th>
<th>Sample B Women</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Contributor</td>
<td>High</td>
<td>Low</td>
<td>35</td>
<td>88</td>
<td>&lt;0.001</td>
<td>51</td>
<td>147</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Equitable Stars</td>
<td>High</td>
<td>High</td>
<td>130</td>
<td>60</td>
<td>&lt;0.001</td>
<td>191</td>
<td>93</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Equitable Laggards</td>
<td>Low</td>
<td>Low</td>
<td>72</td>
<td>119</td>
<td>&lt;0.001</td>
<td>98</td>
<td>187</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Net Extractors</td>
<td>Low</td>
<td>High</td>
<td>117</td>
<td>6</td>
<td>&lt;0.001</td>
<td>168</td>
<td>30</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td><strong>Total Workers</strong></td>
<td></td>
<td></td>
<td><strong>627</strong></td>
<td><strong>965</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows the number of male and female workers who fall in each of four quadrants defined by median productivity and bargaining. Sample A requires a minimum of 30 weeks service while Sample B requires 10 weeks. P-values based on chi-squared tests.

In service, provides similar evidence (see Figure D.2 in Appendix). The joint distribution of peer bargaining and productivity suggests a significant number of workers whose bargaining does not match their productivity.

5.2. Gender and Worker Type

Although the joint distributions of productivity and bargaining traits in our sample shows the substantial variance, this analysis ignores a large literature suggesting that the allocation of tasks and rewards in teams is heavily determined by socio-demographic factors (Babcock et al. 2017, Chatman 2010). Given the largely uniform ethnic makeup of our workers (Han Chinese), we focus on worker gender. Unlike in the United States, salon work in China is relatively evenly split between male and female workers, which allows us to compare how women and men are distributed differently in our four groups.

Table 3 presents the categorization of our two samples by gender for our two samples, and shows remarkable differences by gender in the proportion in each category, formally tested using chi-squared tests. Women are far more likely (32.2%) than men (9.9%) to be “net contributors” with above-median productivity and below-median bargaining outcomes \((p= .001)\), while men are much more likely (33.1%) than women (2.2%) to be “net extractors” who receive better bargaining.
outcomes than their productivity warrants (p<.001). Women are also far less likely to receive equitable bargaining outcomes commensurate with their high performance. They make up only 21.9% of “equitable stars”, while men constitute 36.7% (p<.001). We emphasize that this is not because women are less productive. Although 46.6% of men have high productivity (are “net contributors” or “equitable stars”), 53.4% of women meet this standard, a small and only weakly distinguishable difference (p=0.071). The driving factor behind gender differences in categorization is bargaining outcomes—only 24.1% of women are in the top half of bargaining traits.

The striking difference between male and female workers can be seen in Figure 3, which repeats Figure 2 with breakdown by gender. Although the productivity distributions of women and men are indistinguishable, men dominate the top half of peer bargaining outcomes. Female workers receive considerably lower commission splits, relative to their contributions, compared with male coworkers. Women must reach the 90th percentile of productivity to achieve the bargaining share of the median male worker. The gender disparity is just as severe when examining only card sales productivity. Figure D.3 in the Appendix shows that although women represent the ten most productive card salespeople, they consistently receive worse peer bargaining outcomes than their male counterparts. Figure 4 presents kernel density distributions of total productivity and peer bargaining estimates by worker gender. Women show a weakly higher productivity distributions (Komogorov-Smirnov, p=0.0317), while men have significantly better peer bargaining outcomes (p<0.0001).
We more formally test this gender discrepancy by regressing each worker’s peer bargaining fixed effect on their total productivity fixed effect while controlling for the worker’s age, education and job rank in the organization. It is possible, for example, that the female workers are all of lower rank, younger, or less experienced. We note that since we controlled for job task, rank, and store in the initial regressions that estimated the productivity and peer bargaining fixed effects, they are not omitted variables in these regressions. Our variable of interest is the gender of the worker and the interaction between a dummy for male worker and the productivity fixed effect. Table 4 presents results for regressions that alternatively use service productivity and card sales productivity as dependent variables.

Columns I to III demonstrate how our three different productivity measures correlate with worker bargaining traits in both male and female workers for those workers with at least 30-week observation in our sample period. Male workers consistently have higher bargaining outcomes given their productivity, even when controlling for position, age and education. Moreover, the interaction between being a male worker and card productivity is negative, which signals that card sales productivity is more strongly correlated with bargaining fixed effects for female workers than male workers. Columns IV to VI show consistent results for the sample of workers with at least 10 weeks.

5.3. Predicting Worker Type with Machine Learning

Our results show worker productivity and peer bargaining to be on average unrelated. Furthermore, the relationship between worker gender and the combination of productivity and bargaining is obvious in Figure 3 and Figure 4, suggesting that either social dynamics or gender-specific preferences are important in determining worker type. Our data contain other detailed demographic
Table 4  
Productivity and Bargaining for Different Gender

<table>
<thead>
<tr>
<th>Dependent Variable: Bargaining Fixed Effects</th>
<th>Sample A</th>
<th>Sample B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>Card Productivity ($G_{c_i}$)</td>
<td>0.231***</td>
<td>0.243***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Service Productivity ($G_{s_i}$)</td>
<td>0.368***</td>
<td>0.276***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>All Productivity ($G_{a_i}$)</td>
<td>0.362***</td>
<td>0.305***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Male</td>
<td>0.776***</td>
<td>0.603***</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.129)</td>
</tr>
<tr>
<td>Male $\times G_{c_i}$</td>
<td>-0.152**</td>
<td>-0.199***</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Male $\times G_{s_i}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male $\times G_{a_i}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Worker Characteristics</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>627</td>
<td>627</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.363</td>
<td>0.477</td>
</tr>
</tbody>
</table>

Note: Standard errors, clustered at the store level, are presented in parentheses, with significance levels: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample A (B) requires at least 30 weeks (10 weeks) of observations.

information (e.g., hometown, education level), however, that might also predict productivity and peer bargaining outcomes. Furthermore, our regression approach is descriptive of worker types, rather than a predictive model.

We implement a machine learning model to more formally identify how demographics predict a worker’s combination of productivity and bargaining. Using this approach, we seek to predict three outcomes using separate models: (a) productivity type, which equals one if the worker’s productivity fixed effect is above median; and zero otherwise; (b) peer bargaining type, which equals one if the worker’s bargaining fixed effect is above median, and zero otherwise; and (c) classification type, or in which of the four quadrants lies the worker. The independent variables represent time-invariant worker demographic information: age, gender, education level, applied job title, hometown, starting year, and store.

In order to both model the complex function between workers’ demographic information and their types and to prevent model overfitting, we implement a widely adopted machine learning method, Extreme Gradient Boosted Trees, using the R software package (Chen and Guestrin 2016). Boosted tree models bootstrap a multitude of decision trees in order to classify observations (e.g, our worker types) in each iteration, focusing on maximizing predictive accuracy while correcting for overfitting. In each iteration, this approach builds a decision tree by drawing a bootstrapped sample from the training data and then randomly selects a subset of features that could help to improve the prediction of the outcome variable. Based on these selected features and the bootstrapped samples, the algorithm builds a decision in a greedy way (i.e., maximizes the information gains of
each split from the top of the tree). The algorithm then aggregates across multiple trees to make the final classification. The first substantial benefit of this algorithm over traditional classification methods, such as logistic and probit regression, is that it considers complex interactions between important features and automatically selects out unimportant features. We use an iterative training approach, where in each iteration, the algorithm goes through the training data once to build a decision tree.

The second major benefit is the ability to trade off between in-sample accuracy and out-of-sample prediction power. In particular, the boosting tree algorithm has many “hyper-parameters” such as the depth of the trees, the number of trees in the forest, and the number of features randomly selected in constructing each tree. Depending on the choice of these hyper-parameters, this algorithm can describe functions with different levels of complexity and in turn have different levels of overfitting. For instance, if we allow the algorithm to build trees with many layers and many splits, the algorithm can describe more and more complex functions (from the features to the outcome variables) as the number of layers and splits increase. This means that the algorithm will have higher in-sample accuracy but possibly worse out-of-sample performance since the final model in this case is hugely influenced by the random variations in the training data, which means that the model is overfitted.

In order to prevent overfitting, we use 3-repeats 10-fold cross validation to estimate the out-of-sample prediction errors and search for the optimal hyper-parameters. Intuitively, 10-fold cross validation divides the training sample into 10 pieces. For each piece, the algorithm will train the model based on the other nine pieces of the data and test the algorithm’s out-of-sample prediction power on this remaining piece of the data. Therefore, for each set of hyper-parameters, the algorithm will have 10 performance measures (from 10 pieces) and the algorithm’s overall performance is simply the average of these 10 performance measures. “3-repeats” means that we repeat the above 10-fold cross validation three times with different data divisions and compute the average out-of-sample performance of the model over these three repeats. The out-of-sample performance measures are then used to find the optimal set of hyper-parameters by searching through a grid of hyper-parameters. Once the algorithm finds the optimal set of hyper-parameters on the grid, it will construct the random forest on all data (instead of 9 pieces of the data) using this set hyper-parameters.

We first present results for the two models predicting productivity and peer bargaining traits separately. Panels A and B of Figure 5 represent our in-sample and out-of-sample prediction accuracy for each separate trait. There are several important observations from the figure. First, the out-of-sample error rate of both productivity and the peer bargaining types are well below 0.5 (i.e., the accuracy of randomly guessing), which suggests that worker demographics could help us to
Figure 5  In-sample and Out-of-sample Prediction Errors of Bargaining and Productivity Type

(a) Productivity Type Prediction  
(b) Bargaining Type Prediction  
(c) Productivity and Bargaining Joint Type Prediction

Note: This figure presents the errors for Extreme Gradient Boosted Trees predicting above-median productivity and bargaining as well as worker classification type. Panels A and B show prediction errors for productivity and bargaining type versus 50% counterfactual, respectively. Panel C shows prediction errors for the four worker types versus 75% counterfactual.

pre-classify workers into different quadrants. Second, we observe that, as the number of iterations increases, the in-sample error continues to fall while the out-of-sample errors stabilize. This suggests that, if we did not use cross-validation to find the best hyper-parameters, our model would suffer from severe over-fitting problems, which demonstrates the value of machine learning models in minimizing out-of-sample errors. Third, we observe that the out-of-sample errors are considerably lower for peer bargaining types than productivity types. As we will show later, this is because gender is a very strong predictor of the bargaining type while only weakly predicting productivity. This is consistent with our previous analysis that female workers are consistently receiving lower bargaining cuts compared to male workers. Moreover, Panel C of Figure 5 shows the in-sample and out-of-sample errors for our random forest algorithms to classify the joint types. Similarly, we find that the out-of-sample errors of the algorithms are well below the errors from randomly guessing (i.e., 75%), and that the algorithm is prone to overfitting.

Last, we analyze the prediction algorithms in depth to demonstrate which worker demographics account for the difference in prediction power between the two traits. In particular, following
5.4. Evidence on Mechanisms Behind Gender Inequality

Theory and prior empirical evidence provide several possible mechanisms behind the consistently lower peer bargaining outcomes for women observed in our data. As our model represents, these differences could be partly due to stronger prosocial preferences in women, and could also result from lower bargaining power.

To help identify which mechanisms explain our results, we first present the raw commission splits based on the gender mix in teams of two: all-female, all-male, and mixed-gender. Panel A of Figure 7 presents a kernel density plot of the commission split. Half of all cards sold by all-female teams result in a 50-50 commission split, while in all-male teams, less than 30% of transactions result in a 50-50 commission split. These raw data suggest that in same-sex teams, women tend
Figure 7  

All-Female Teams More Likely to Split Commissions Evenly
Equality of Transactions with Different Teams

(a) Splits for All-Female and All-Male Teams

Transaction Cuts in Mixed-gender Groups

(b) Splits for Female and Male Workers in Mixed Team

Note: This figure presents kernel density plots of raw data on bargaining splits in two-person card sales teams. Panel A shows the distributions in same-gender teams. Panel B shows mixed-gender teams.

to have a much stronger preference for equality than do men. Panel B of Figure 7 shows the splits for male and female workers in mixed gender teams. The splits are less likely to be 50-50 in mixed gender teams compared to all-female teams. Moreover, females are receiving disproportionately less commission compared to male workers in mixed-gender teams.

The result from Panel A is consistent with the argument that female workers have higher inequality aversion and that these distribution preferences push them to seek more equal splits. We note, however, that prosocial preferences are unlikely to also produce the results in Panel B, where mixed-gender teams produce advantageous results for men.
To further explore these mechanisms, we repeat the regression in Equation 4, estimating for each worker separate bargaining fixed effects for partnerships with male \((C_{im}^m)\) and female \((C_{if}^f)\) coworkers. This approach, similar to the discrimination measure used in Gino and Pierce (2010b), allows us to understand differential outcomes \((C_{im}^m - C_{if}^f)\) based on with whom the worker interacts. We necessarily restrict our sample to workers with at least ten card transactions with both male and female coworkers.

We present the distribution of these fixed effects for female and male workers in Figure 8 and Figure 9. Figure 8, which shows the four distributions of bargaining fixed effects by worker and partner gender, confirms that female workers consistently receive lower shares when working with both men and women, but it also confirms that the presence of a female worker in a team reduces the variance of outcomes. Figure 9 presents each worker’s unique pair of bargaining fixed effects, and shows a relatively tight distribution around the diagonal. This indicates that although most workers consistent receive better bargaining outcomes when working with women, there is little variation in the size of this advantage across workers.

To more formally test for preference- and power-based mechanisms, we conduct a large-scale simulation where we vary the gender-specific prosociality \((i.e., \alpha_{male, \beta_{male}}, \alpha_{female, \beta_{female}})\) and bargaining power of male and female workers \((i.e., the proposing probability of male workers)\). In particular, we observe two important moment conditions in Figure 7:
Figure 9  Gender-Specific Bargaining Estimates for 515 Workers
Bargaining FE by Gender and Coworker Gender

Note: This figure shows the unique partner-gender-specific estimate for 515 workers with a minimum of ten card transactions with peers of each gender. Blue (pink) dots represent male (female) workers. Vertical and horizontal lines represent medians. Linear fit with 95% confidence intervals.

1. Panel (a) of Figure 7 shows that, in same-gender groups, the average standard deviation of female-to-female splits is much smaller than that of male-to-male splits. In other words, females are more likely to split around 50%.

2. Panel (b) of Figure 7 shows that, in mixed-gender groups, male workers’ splits are much larger than those of female workers.

The simulation, presented in detail in the Appendix, numerically shows that female workers need to have both lower bargaining power and higher prosociality to explain the 2 aforementioned observations about the moments in Figure 7.

5.5. Robustness Check of Endogenous Team Formation

One natural concern with our data is that we cannot directly observe the process through which production teams are formed. If workers endogenously select into teams based on similar productivity, the service productivity estimators \( G_s^i \) do not purely capture a worker’s productivity, but instead also reflect her consistent pairing with similar workers. A similar problem would occur if managers were strategically pairing workers based on productivity. Such endogeneity problems would potentially endanger our main claim that female workers consistently receive lower bargaining outcomes compared to male workers with comparable productivity. In particular, our results will be confounded if female workers tend to work with more productive coworkers, and there is a positive productivity spillover. In this case, since female workers tend to work with more productive coworkers, their true productivity is lower than the estimated productivity due to positive
productivity spillovers. Therefore, the observation that female workers have lower bargaining ability than men with similar estimated productivities may be because female productivity is biased downward.

To formally explore this possible issue, we use service transactions with two-person teams (80.2% of all multi-worker service transactions) and compute each worker’s average teammate productivity for each week. If female workers indeed tend to work with more productive workers and in turn have upwardly biased productivity fixed effects, we should find that female workers have higher coworker productivity. Table 5 shows the results of regressing average coworker productivity on worker gender. Columns I and II use our smaller sample requiring 30 weeks, while Columns III and IV use the larger 10 week sample. The regressions show that whether or not one controls for observable characteristics, female gender appears to negatively correlate with coworkers’ average productivity. This suggests that female workers tend to work with less productive coworkers. This suggests that, even though there may be some endogenous staffing effects in the data, this endogeneity would bias against our results, which suggests that our estimates of male and female pay inequity may be more conservative than the true effect.

<table>
<thead>
<tr>
<th>Table 5 Robustness Check of Endogenous Team Formation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coworkers’ Average Productivity</td>
</tr>
<tr>
<td>Sample A</td>
</tr>
<tr>
<td>I</td>
</tr>
<tr>
<td>Female</td>
</tr>
<tr>
<td>(0.054)</td>
</tr>
<tr>
<td>Worker Characteristics</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R²</td>
</tr>
</tbody>
</table>

Note: Robust standard errors presented in parentheses, and are not clustered so as to provide a conservative identification test. *p<0.1; **p<0.05; ***p<0.01. Sample A (B) requires at least 30 weeks (10 weeks) of observations.

6. Implications for Firm Performance

Our results have clear and obvious implications for inequitable outcomes for women in the workplace. But what are the organizational implications of the many inequitably compensated workers in data? In the short-run, the four types of workers can be ordinally ranked by their value to the firm. Net contributors are the most valuable, because they extract substantially less value from the firm than their high productivity justifies. We note that if a net contributor’s low peer bargaining trait is determined by prosocial or equitable preferences, their bargaining type is voluntary. If their peer bargaining trait is low because of low bargaining ability or social determinants, this position is undesired. In contrast, net extractors are the least valuable to the firm. They have low productivity, yet achieve high peer bargaining outcomes that allow them to extract inequitably high value.
Equitable stars and equitable laggards are both less valuable to the firm than net contributors, but dominate net extractors. Equitable stars are likely to be more valuable than equitable laggards for several reasons. First, since labor and capital are complementary inputs to firm productivity, high productivity labor will require less capital per unit produced. Second, if high productivity workers generate peer effects (Mas and Moretti 2009) or knowledge spillovers (Azoulay et al. 2010, Chan et al. 2014b, Song et al. 2017), equitable stars are likely to improve the productivity of those around them in ways that equitable laggards would not. Finally, due to natural wage compression within firms (Nickerson and Zenger 2008) and firm-specific human capital (Jovanovic 1979), equitable stars will tend to be underpaid relative to their productivity advantage.

Although there is a clear hierarchy in the immediate value of each worker type for the firm, it presents more complex long-run implications based on social comparison and outside labor market options. Psychologists and economists have long recognized that employees engage in social comparisons with coworkers (Festinger 1954), with one of the key comparisons being the assessment of the fairness or equity of their own rewards and contributions versus their peers (Carrell and Dittrich 1978, Akerlof and Yellen 1990).

The net extractors and net contributors are likely to produce perceptions of inequity, since their bargaining traits are not rewarding them commensurate with their contributions through productivity. Net contributors may not perceive inequity, since they may have low peer bargaining traits because of preferences. But if their peer bargaining traits are due to ability or social determinants, perceptions of inequity are inevitable. Net extractors, however, will generate widespread perceptions of inequity because their rewards relative to contributions will exceed each of the other three worker types. Equitable stars, for example, will observe net extractors receiving equivalent peer bargaining outcomes despite substantially lower contributions through productivity.

Recent work has explained exactly how costly such widespread social comparison can be for firm performance when it reveals inequity (Larkin et al. 2012, Cohn et al. 2014, Gartenberg and Wulf 2017). Wage and other reward comparisons can generate feelings of envy that can reduce effort and increase turnover (Nickerson and Zenger 2008, Card et al. 2012, Obloj and Zenger 2017). Perceptions of inequity can also increase unethical behavior and misconduct (Gino and Pierce 2009, 2010b, Edelman and Larkin 2014, John et al. 2014, Larkin and Pierce 2015), and can even demotivate employees across unrelated tasks (Gubler et al. 2016).

Even in the absence of social comparison, the decoupling of productivity and peer bargaining can hurt the firm through attrition to outside labor markets. If net contributors consistently receive less value than their peers because of either bargaining ability or social determinants, they are likely to look for outside employment where peer bargaining is less determinant of the rewards structure. For example, net contributors may seek employment in firms where their productivity...
is directly rewarded and where their peer bargaining weakness is irrelevant because of task and reward assignment is either standardized or hierarchically assigned by managers. This process, whereby net contributors leave the firm, saps the firm of some of its most productive workers and leaves it with a disproportionate number of low productivity workers.

7. Conclusion

In this paper, we argued that two persistent traits are crucial in determining the value of a given employee in team-based production: their productivity in crucial tasks and their bargaining outcomes with peers. Our evidence from productivity and commission split bargaining among Chinese salon workers validates that there is indeed significant heterogeneity and explanatory power in these persistent traits—they explain 16.46% of the variance in productivity and 8.0% in commission splits. Just as importantly, our results imply that measuring a worker’s net contribution purely on productivity ignores a crucial orthogonal dimension—the value extracted by the worker for that productivity.

These initial results, however, ignore a crucial predictor of their joint distribution—employee gender. In our sample, male workers consistently extract advantageous bargaining values from their female coworkers, despite having no observable productivity advantage. Consistent with overwhelming evidence on pay inequity, women in our sample earn less than their contributions would merit. And as Castilla and Benard (2010) highlight, this occurs even in the context of a pay-for-performance system. The uniqueness of our results, however, is that this inequity also results from bargaining outcomes with peers. Although we can only observe bargaining on commission splits, we believe the implications apply more broadly to inequitable task and effort divisions in teams as well (Babcock et al. 2017). A broad literature on married couples, for example, consistently finds that even as wives increase professional success and earnings relative to their husbands, they continue to contribute disproportionately to household labor and child-rearing (Pollak 1985).

We note that our machine learning models directly address the common concern that that correlations observed in regression models might be spurious. Standard errors in team- or network-based studies are notoriously difficult to estimate (Gel et al. 2017, Snijders and Borgatti 1999), and even with our cluster correction at the worker level we might be concerned that the joint distribution of productivity and bargaining fixed effects simply reflects noise. Our machine learning approach, however, provides validation that productivity and peer bargaining traits are meaningful and predictable based on observable worker characteristics. Most clearly, we can be confident that women’s consistently lower bargaining outcomes are driving our classification.

Like most field studies, our results from China are embedded in a specific culture with unique norms and preferences around bargaining, fairness, and gender roles. Extensive work shows differences across cultures in coworker interaction (Tinsley and Brett 2001), negotiation strategies and
outcomes (Gunia et al. 2011, 2016, Kopelman et al. 2016), and most specifically around fairness or equality (Gelfand et al. 2002). Furthermore, the gender pay inequality we observe is specific to China. Social scientists have found broad differences in pay equity across countries (Blau and Kahn 2003). We note, however, that this literature has typically found more equal negotiation outcomes in China than in Western countries (e.g., Tinsley and Pillutla 1998), which would suggest greater bargaining trait variance in settings different from our own. As the world’s largest economy with twenty percent of world population, even culturally specific results are important and generalizable.

We note several limitations of our study. First, we cannot observe why these workers choose to join or leave the salons, nor the process through which teams are assigned. Our identification tests show little evidence, however, that worker teams strategically form based on productivity. So we are doubtful that strategic staffing decisions are seriously biasing our results, but we cannot fully dispel this concern. Second, we cannot observe any exchange between coworkers that occurs outside our data. It is possible, for example, that workers may give financial or other side payments in exchange for larger bargaining shares in commissions.

Finally, we note that if worker bargaining traits are known by coworkers, then those with inequitably high bargaining outcomes may impose an additional cost to the firm—decreased joint gains (Tinsley et al. 2002). Workers anticipating a poor commission split may focus less effort on card sales with coworkers that they know will likely extort unequal commission shares. Furthermore, the income equality observed in our firm may represent broader costs to society detailed in extensive literature on wage and workload inequity.

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Appendix

A. Simulation on Bargaining Outcomes

In order to understand what mechanisms drive the results in Figure 7, we conduct a large-scale simulation. In particular, we observe two important moment conditions in Figure 7:

1. Panel (a) of Figure 7 shows that, in same-gender groups, the average standard deviation of female-to-female splits is much smaller than that of male-to-male splits. In other words, females are more likely to split around 50%.

2. Panel (b) of Figure 7 shows that, in mixed-gender groups, male workers’ splits are much larger than those of female workers.

Therefore, we design a simulation method by varying the proposociality of male and female workers (i.e., \( \alpha_{\text{male}}, \beta_{\text{male}}, \alpha_{\text{female}}, \beta_{\text{female}} \)) and the bargaining power of male and female workers (i.e., the proposing probability of male workers).

In this simulation, we have 5 parameters:

1. Prosociality of male workers: \( \alpha_{\text{male}} = \beta_{\text{male}} \sim \text{Uniform}(0, x_{\text{male}}) \)
2. Prosociality of female workers: \( \alpha_{\text{female}} = \beta_{\text{female}} \sim \text{Uniform}(0, x_{\text{female}}) \)
3. Proposing probability of male workers: \( p_{\text{male}} = 1 - p_{\text{female}} \)
4. Outside options of male workers: \( r_{\text{male}} \sim \text{Uniform}(0, \bar{r}_{\text{male}}) \)
5. Outside options of female workers: \( r_{\text{female}} \sim \text{Uniform}(0, \bar{r}_{\text{female}}) \)

In the simulation, we assume that \( \bar{r}_{\text{male}} = \bar{r}_{\text{female}} = 0 \) (i.e., both female and male workers have outside options 0) and \( x_{\text{male}} = 0 \) (i.e., male workers are always not prosocial). We vary \( x_{\text{female}} \) from 0 to 0.5. We also vary \( p_{\text{male}} \) from 0.5 (i.e., male and female workers have same bargaining power) to 0.9 (i.e., male workers have much higher bargaining power). For each set of parameters (i.e., \( (x_{\text{male}}, x_{\text{female}}, p_{\text{male}}, \bar{r}_{\text{male}}, \bar{r}_{\text{female}}) \)), we randomly draw 1,000 samples of \( (\alpha_{\text{male}}, \alpha_{\text{female}}, p_{\text{male}}, \bar{r}_{\text{male}}, \bar{r}_{\text{female}}) \) and report the average split of male workers in mixed gender groups, the standard deviations of splits in all-male and all-female groups. Figure A.1 shows the simulation results.

Panel (A) in Figure A.1 shows the difference between male splits and female splits in the mixed-gender groups with respect to female workers’ prosociality and bargaining power of male workers (i.e., the probability of proposing for male workers). The upper-left corner of the graph shows that, if female and male workers are equally prosocial and they have the same proposing probability, female and male workers’ split difference is precisely at 0. The vertical direction of the graph shows that the difference of average splits becomes larger and larger when the male workers have higher proposing probability (i.e., higher bargaining power). However, the horizontal direction of the graph shows that the difference of average splits do not change much if female becomes more prosocial. This suggests that, in order for us to rationalize the data where male workers have higher bargaining outcomes than female workers, we need male workers to have higher bargaining power.

\[\text{Bargaining power can also be represented by the outside options of female and male workers (} r_{\text{male}} \text{ and } r_{\text{female}}) \text{. Our simulation results hold if we use outside options to represent bargaining power instead of the proposing probability.}\]

\[\text{Our simulation results hold qualitatively if we use different outside option levels or different prosociality levels for male workers.}\]
Figure A.1 Simulation of Male and Female Bargaining Outcomes

(a) Male-to-female Split Average Difference in Mixed-Gender Groups
(b) Male-to-female Split Standard Deviation Difference in Same-Gender Groups

Note: This figure presents the average splits between male and female workers in mixed-gender groups as well as the average difference between standard deviations of male and female splits in same-gender groups for different prosociality levels as well as different proposing probabilities. Each point represents 1,000 simulations.

Panel (B) in Figure A.1 shows the difference between the standard deviations of male workers’ and female workers’ splits in the same-gender groups with respect to female workers’ prosociality and bargaining power of male workers. Again, the upper-left corner in the heat map is 0, suggesting that, when female and male workers have the same bargaining power and prosociality, they have the same standard deviation of splits in the same-gender groups. The vertical direction of the graph shows that the difference of standard deviations do not change with respect to one gender’s bargaining power. However, the horizontal direction of the graph shows that this difference changes dramatically when one gender becomes more prosocial. This suggests that, in order to match the data that female workers have much lower standard deviation of splits in the same-gender groups, we need female workers to be more prosocial than male workers.

In summary, this simulation numerically shows that female workers need to have lower bargaining power and higher prosociality to rationalize the 2 aforementioned observations in Figure 7.

B. Proof of Proposition 1:

Let us first analyze the decision by the responder given an offer \( s \). If \( s \geq 0.5 \), the utility of accepting \( s \) for the responder is \( u_r(s) = s - \beta_r(2s - 1) \). If \( \beta_r < 0.5 \), \( u_r(s) \) is always greater than or equal to 0.5, which means that \( u_r(s) \) is always greater or equal to \( r_r \). If \( \beta_r \geq 0.5 \), we need \( s \leq \frac{r_r - \beta_r}{1 - 2\beta_r} \). Since \( s \leq \frac{r_r - \beta_r}{1 - 2\beta_r} \) is bounded above by \(-0.5\) for \( \beta_r \in [0.5, 1] \) and \( r_r \in [0.0, 0.5] \), there is always no trade when \( \beta_r \geq 0.5 \).

Similarly, if \( s < 0.5 \), the utility of the responder is \( u_r(s) = s - \alpha_r(1 - 2s) \), which is greater than the outside option if \( s - \alpha_r(1 - 2s) \geq r_r \), or \( s \geq \frac{r_r + \alpha_r}{1 + 2\alpha_r} \). This means that the responder only accepts the offer if the offer is big enough.

Given the responder’s reaction, we can compute the proposer’s exact optimal strategy since this is a complete-information game. First notice that the fact that \( \beta_s \leq 1 \) requires that proposer to at most offer
s = 0.5. This is because if $\beta_i \leq 1$, the proposer will always benefit by offering $s = 0.5$ instead of $s > 0.5$. Moreover, notice that if $s > 0.5$ will be accepted by one responder, then $s = 0.5$ will always be accepted by the same responder. Therefore, when the proposer is prosocial enough $\beta_s > 0.5$, he prefers offering $s = 0.5$.

If the proposer is not prosocial enough, he will offer $s < 0.5$, and his utility is $u_s = (2\beta_s - 1)s + (1 - \beta)$. Since the proposer can only offer when his share from the game is greater than his outside option, he will only offer $s$ if $(2\beta_s - 1)s + (1 - \beta) \geq r_s$, which is $s \leq \frac{1 - \beta_s - r_s}{1 - 2\beta_s}$. This means that the offer has to be small enough for the proposer to benefit from the game. Therefore, combing this with the responder’s action, the proposer will always offer the lowest possible offer, which is $\frac{r + \alpha_s}{1 + 2\alpha_r}$ if the offer is lower than the proposer’s break-even point $\frac{1 - \beta_s - r_s}{1 - 2\beta_s}$. In other words, if $\frac{1 - \beta_s - r_s}{1 - 2\beta_s} \geq \frac{r + \alpha_s}{1 + 2\alpha_r}$, $s = \frac{r + \alpha_s}{1 + 2\alpha_r}$. Note that $\frac{1 - \beta_s - r_s}{1 - 2\beta_s} \geq 0.5$ for $\beta_s < 0.5$ and $\frac{r + \alpha_s}{1 + 2\alpha_r} \leq 0.5$, therefore, the condition is always satisfied.

In summary, since $u_s = (2\beta_s - 1)s + (1 - \beta)$ is decreasing in $s$ if $\beta_s < 0.5$. This means that the proposer will offer the smallest possible $s < 0.5$ when $\beta_s < 0.5$, which is $\frac{r + \alpha_s}{1 + 2\alpha_r}$. If $\beta_s \geq 0.5$, the proposer will offer $s = 0.5$, and this offer is only accepted by the responder if $\beta_r < 0.5$.

C. Proof of Lemma 1:

We first prove that agent $i$’s payoff from the game is weakly increasing in $p_i$, i.e., his probability of being the proposer. This is intuitive, since if an agent is a proposer, he will always get $0.5$ ($\beta_i \geq 0.5$) or above ($\beta_i < 0.5$), when there is a trade. This is because $\frac{r + \alpha_i}{1 + 2\alpha_r}$ is bounded above by $0.5$ for all feasible primitives. However, if an agent is a responder, when there is a trade, he will at most get $0.5$. Therefore, an agent’s average payoff increases when he is proposer compared to a responder. The weak increase happens when there is no trade regardless whether the agent is a proposer or a responder.

Second, let us prove that if an agent $i$ has higher outside option $r_i$, he will receive a higher outcome when bargaining with a pool of agents. This is also intuitive. When the agent $i$ is bargaining with other agents, regardless whether he is a proposer or a responder, his split is bounded below by $r_i$. Therefore, when $r_i$ increases, the lower bound of the bargaining outcome increases. Since $r_i$ does not change the bargaining outcome except setting the lower bound, the agent will get a higher split when $r_i$ increases.

Third, let us show that the average outcome is weakly increasing in $\alpha_i$. Notice that when agent $i$ is the proposer, his payoff does not depend on $\alpha_i$. If the agent is a responder, his average payoff is increasing in $\alpha_i$ since he will be willing to only accept a higher offer when $\alpha_i$ increases.

Last, let us show that the average outcome is weakly decreasing in $\beta_i$. Notice that when one agent $i$ is a proposer, he will get on average less payoff, if $\beta_i \geq 0.5$ versus $\beta_i < 0.5$. If the person is a responder, he will have some probability to get $0.5$ if $\beta_i > 0.5$. And he will not get $0.5$ if $\beta_i \geq 0.5$. Since $0.5$ dominates all of agent $i$’s payoffs regardless of the opponent when the agent is a responder, the agent’s average payoff decreases when $\beta_i$ increases.

D. Auxiliary Graphs and Tables
<table>
<thead>
<tr>
<th>Variable</th>
<th>No. of Obs</th>
<th>Mean</th>
<th>Std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Two-employee Card Transactions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue</td>
<td>38,282</td>
<td>2,345.704</td>
<td>2,755.105</td>
<td>8.000</td>
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</tr>
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<td>Commission</td>
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<td>123.348</td>
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<td>0.232</td>
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<tr>
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<td>16.899</td>
<td>3.720</td>
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<td>Month</td>
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<tr>
<td>Year</td>
<td>38,282</td>
<td>2011.7</td>
<td>0.940</td>
<td>2009</td>
<td>2013</td>
</tr>
<tr>
<td>New Card</td>
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<td>0.500</td>
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<td>Panel B: Service Transactions</td>
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<td></td>
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<td></td>
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<td>1,024,417</td>
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<td>Panel C: Worker Characteristics</td>
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Note: The table contains all observations related to the 502 male workers who have at least worked 10 weeks in our sample period. The unit of observation is employee-transaction. Therefore, for each transaction in Panel A and Panel B, there may be multiple observations, depending on whether this transaction is completed by multiple employees.
Table D.2  Summary Statistics of All Transactions for Female Workers

<table>
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<tr>
<th>Variable</th>
<th>No. of Obs</th>
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<th>Std</th>
<th>Min</th>
<th>Max</th>
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<td>Panel A: Two-employee Card Transactions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue</td>
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<td>10.000</td>
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<td>3.695</td>
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</tr>
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<td>Weekend</td>
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<td>0</td>
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</tr>
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<td>3.535</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
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<td>0.883</td>
<td>2009</td>
<td>2013</td>
</tr>
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<td>New Card</td>
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<td>0.481</td>
<td>0.500</td>
<td>0</td>
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</tr>
<tr>
<td>Panel B: Service Transactions</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>No. of Workers</td>
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<td>Commission</td>
<td>553,537</td>
<td>22.124</td>
<td>40.081</td>
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<td>1,315</td>
</tr>
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<td>Hour</td>
<td>553,537</td>
<td>17.355</td>
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<td>Weekend</td>
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<td>0.347</td>
<td>0.476</td>
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<tr>
<td>Month</td>
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<td>6.395</td>
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<tr>
<td>Year</td>
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<td>2011.6</td>
<td>0.987</td>
<td>2009</td>
<td>2013</td>
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<tr>
<td>Appointment</td>
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<td>0.250</td>
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<td>Junior Worker</td>
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<td>0.539</td>
<td>0.499</td>
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<tr>
<td>Senior Worker</td>
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<td>0.056</td>
<td>0.229</td>
<td>0</td>
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<tr>
<td>Intern Worker</td>
<td>553,537</td>
<td>0.056</td>
<td>0.230</td>
<td>0</td>
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</tr>
<tr>
<td>Beautician</td>
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<td>0.331</td>
<td>0.470</td>
<td>0</td>
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<tr>
<td>Product Sale</td>
<td>553,537</td>
<td>0.019</td>
<td>0.137</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Panel C: Worker Characteristics</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Age</td>
<td>463</td>
<td>26.72</td>
<td>3.83</td>
<td>19</td>
<td>45</td>
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<tr>
<td>Start Year</td>
<td>463</td>
<td>2010.7</td>
<td>1.05</td>
<td>2009</td>
<td>2013</td>
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<tr>
<td>High School Education</td>
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<td>0.28</td>
<td>0.45</td>
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</table>

Note: The table contains all observations related to the 463 female workers who have at least worked 10 weeks in our sample period. The unit of observation is employee-transaction. Therefore, for each transaction in Panel A and Panel B, there may be multiple observations, depending on whether this transaction is completed by multiple employees.
Figure D.2 Joint Distribution of Productivity and Peer Bargaining Fixed Effects for Workers (Workers with more than 10 weeks service)

Note: This figure shows the unique bargaining and card productivity estimates for each of the 965 workers with at least 10 weeks of service and 10 card transactions. Vertical and horizontal lines represent medians. Included is a linear fit ($\beta=.305$, $SE=.0289$) with 95% confidence intervals. The slope of the linear fit is significantly different from 0 ($p<0.0001$).

Figure D.3 The Joint Distribution of Card Sales Productivity and Peer Bargaining Fixed Effects by Gender

Note: This figure shows the unique bargaining and card productivity estimates for each of the 627 workers with at least 30 weeks of service and 30 card transactions. Men are represented in blue, while women are pink. Vertical and horizontal lines represent medians. Included is a linear fit with 95% confidence intervals. The slope of the linear fit is significantly different from 0.
Figure D.4  Worker Productivity and Bargaining Types

Note: This figure presents four worker types based on productivity and peer bargaining traits.