Social Comparison and the Value of Performance Trajectory Information: A Field Experiment in the Workplace*

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Abstract

Many new employees leave their organizations before realizing the returns to experience. One reason is that they often lack information about how performance evolves with tenure, reducing their willingness to stay. We examine whether providing new workers with such information can improve retention and firm performance. In a large-scale randomized controlled trial at a leading multinational spa chain in China, we sent workers twice-weekly information for 28 weeks showing the performance trajectories of their high-performing senior coworkers. The intervention reduced new worker attrition by 11-12% and increased revenue by 15% in stores with higher shares of new workers. These effects are mostly driven by reduced stress and improved mental health among new workers, as the intervention lowered their beliefs about senior coworkers' performance during the early stages of their careers. By contrast, sharing only the current performance of a similar-tenure peer had no detectable effects. Overall, this study demonstrates that showing junior workers the "*Curricula Vitae*" of senior workers mitigates social comparison costs within firms.

JEL Codes: J24, J63, M12, M50, M54

Keywords: social comparison, experience curve, employee retention, performance transparency, field experiment

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1 Introduction

Gaining experience benefits both workers and their firms. For firms, workers with firm-specific experience facilitate organizational learning (Argote and Miron-Spektor, 2011; Huckman and Pisano, 2006), reduce turnover costs, and improve productivity (Hatch and Dyer, 2004). For workers, accumulating experience within a firm typically leads to higher compensation and greater career advancement opportunities (Kwon and Milgrom, 2014; Morris et al., 2017).

Firm management generally understands the return to experience through access to internal and industry data, which they use to inform performance forecasts and strategic decisions.[1] By contrast, workers, especially new hires, often lack such information. What is most salient in the workplace is typically the current performance of their coworkers, particularly the highly performing senior ones. Yet the early-career performance of these senior workers, which is crucial for inferring the return to experience, occurred before the new workers joined and is usually not disclosed.

When new workers lack information about the return to experience within their firm, they may form distorted beliefs. Psychological research on the fundamental attribution bias suggests that people tend to over-attribute others' success to innate ability while under-attributing it to learning or effort (Horn and Loewenstein, 2025; Ross, 1977). Such distorted beliefs can have two adverse consequences. First, overestimating the innate ability of high-performing senior workers may lead new workers, through upward social comparison, to feel inferior, thereby increasing stress and harming mental health (Larkin et al., 2012). Second, underestimating the scope for learning-by-doing may lead new workers to believe that their own performance will not improve much with experience. Both mechanisms can produce suboptimal outcomes, such as premature attrition, that prevent both the workers and the firm from realizing the full benefits of experience, leading to inefficiencies in talent development and higher turnover costs (Campbell et al., 2012).

Can firms reduce early-career attrition by making the returns to experience more visible to new workers? To address this question, we design a 28-week randomized controlled trial (RCT) at a leading multinational spa chain with 160 stores and more than 7,000 spa workers in its Chinese division. This company

[1] For example, firms use return-to-experience information to forecast performance at higher output levels (Darr et al., 1995). Such forecasts guide strategic choices in pricing, capacity investment, workforce training, and process improvement (Eggers, 2012; Henderson and Cool, 2003; Ryu et al., 2022), helping firms build firm-specific capabilities and competitive advantage (Chen et al., 2021; Lapré and Tsikriktsis, 2006).

is well suited to study our question for two reasons. First, service workers often face a long experience curve before reaching their potential, as is representative of many other industries; Figure 1 illustrates the typical tenure–performance trajectory in our setting. Second, upward social comparison is prevalent because spa workers share the same individual, performance-based compensation scheme, occupy roles of similar responsibility, and compete for the same pools of resources and promotion, conditions that are known to induce social comparison (Kulik and Ambrose, 1992). In this firm, the organizational structure is flat, and most service workers remain in the same role over time, so comparisons occur primarily within a position rather than across positions. In a pre-RCT survey, 71% of workers reported often comparing their performance to coworkers, and 58% reported using high-performing coworkers as their reference targets (see Figures A1 and A2).

[INSERT FIGURE 1]

In the main treatment of our RCT, all workers from 40 randomly selected stores were assigned to the *performance trajectory group*. Twice weekly during the treatment period, they received information about the performance trajectory of an anonymous high-performing senior coworker in their region. This treatment is designed to fill in the "big picture" for workers when they compare themselves to senior colleagues.

We measure the effects of the information treatment on a variety of outcomes, both at the store level and the worker level. Administrative data provide detailed records on store revenues, worker attrition, performance, and salary. We complement these with survey data on beliefs and subjective well-being collected throughout the treatment period. These consolidated datasets allow us to estimate the effects of performance trajectory information and examine the underlying mechanisms.

The first main result is that performance trajectory information significantly reduces attrition among new workers by 11–12%, with no detectable impact on senior workers. Second, while the average treatment effect on store revenue is modest, stores with above-median shares of new workers experience revenue gains of around 15%. This pattern suggests that making the experience curve visible is particularly beneficial where a larger share of the workforce is still near the start of their performance trajectory.

Zooming in on mechanisms, our third main result shows that the treatment's effect on attrition is mediated by reductions in stress and improvements in mental health, consistent with the hypothesized social comparison channel. Moreover, the stress-reduction effect is particularly pronounced when the disclosed trajectory begins at a low performance level. This pattern supports our interpretation that new workers' social comparison costs stem from their beliefs about the innate abilities of high-performing senior coworkers.

Do these benefits arise from informing new workers about the early-stage performance of any coworkers, or are they specific to information about high-performing senior coworkers? To address this question, we conduct a parallel treatment on all workers from 40 additional randomly selected stores. This treatment mirrors the trajectory treatment, except that the twice-weekly messages provide recent performance information about a coworker in the same region and with similar tenure. We find few, if any, effects on any workplace outcomes for this group. This result indicates that performance trajectory information is effective specifically when it features high-performing senior workers, supporting our premise that *upward* social comparison is the key mechanism. Finally, we conduct additional analyses to rule out alternative explanations, including shifts in beliefs about future performance, reduced uncertainty among risk-averse workers, increased competitiveness, and Hawthorne effects. None of these mechanisms account for the observed treatment effects.

This paper contributes to the burgeoning literature investigating the effects of social comparison on employee performance. Recent studies provide evidence that social comparison can impose substantial costs on firms, including increased turnover (Carnahan et al., 2012; Kacperczyk and Balachandran, 2017), lower effort (Cullen and Perez-Truglia, 2022), reduced productivity (Obloj and Zenger, 2017), lower job satisfaction (Card et al., 2012), and even unethical or risk-taking behaviors (Edelman and Larkin, 2015; Kacperczyk et al., 2015; Siegel and Hambrick, 2005). While prior work has primarily examined the consequences of social comparison, we shift the focus to identifying practical solutions to reduce its adverse effects. A central trade-off in upward social comparison is between its positive effect on motivation and its negative effect on stress (Larkin et al., 2012). Our results show that the latter can be mitigated by providing senior workers' historical performance trajectories. In addition, conceptually, our study extends the literature beyond purely vertical comparisons (e.g., with supervisors) and horizontal comparisons (e.g., with same-level peers) (Cullen and Perez-Truglia, 2022; Gartenberg and Wulf, 2017; Kacperczyk and Balachandran, 2017) to what we term *temporal horizontal comparison*: a form of social comparison in which junior workers evaluate themselves against the past performance of more-senior peers at comparable tenure stages.

This study adds to a recent and rapidly growing literature on the impact of pay transparency and pay inequality (Fahn and Zanarone, 2022; Fredrickson et al., 2010; Gutierrez et al., 2025; Kalyta, 2009). The growing use of performance-based pay has contributed to rising income disparities across occupations and firms (Cuñat and Guadalupe, 2009; Lemieux et al., 2009). Prior work has documented how pay transparency affects employee behavior and organizational outcomes using experimental and quasi-experimental methods (e.g., Breza et al., 2018; Lyons and Zhang, 2023; Sharkey et al., 2022). Our study advances the existing literature by introducing information about coworkers' performance trajectories as an additional instrument, effectively expanding the space of pay transparency. More importantly, whereas most prior research has focused on revealing coworkers' or managers' current pay or performance levels, we highlight the value of showing coworkers' performance trajectories starting from early tenure stages.

Third, this paper engages with the foundational theoretical literature on career concerns and wage dynamics (e.g., Dewatripont et al., 1999; Gibbons and Murphy, 1992; Lazear and Rosen, 1981). The central idea of this work is that workers care about not only current incentives but also future prospects. Recent strategy scholarship extends these ideas to settings such as technological opportunities, inventor behavior, and collaboration choices (Piezunka and Grohsjean, 2023; Tandon and Toh, 2022). We complement this work by examining social comparison and career concerns within a single field setting and providing causal evidence that disentangles their effects.

Finally, this paper contributes to the literature on how management practices influence employee retention, well-being, and productivity. Foundational studies have emphasized the strategic value of human resource practices for organizational performance (Ichniowski et al., 1997; Koch and McGrath, 1996). Building on this foundation, more recent research highlights how data-driven and behavioral approaches can improve managerial decisions and shape workforce outcomes (Gambardella et al., 2015; Ranganathan and Benson, 2020). Our study complements this work by showing that a simple and cost-effective data-driven intervention that provides insight into coworkers' performance paths can meaningfully reduce turnover. In doing so, we contribute to the growing body of evidence on how pay structure and information disclosure shape retention (Friebel et al., 2023; Sandvik et al., 2021), and extend research on how peer dynamics and psychological stress influence workplace behavior (Cahlíková et al., 2020).

The remainder of this paper is organized as follows. Section 2 develops a theoretical framework and derives testable hypotheses to guide the empirical analysis. Section 3 describes our context and lays out the experimental design, data, and econometric framework. Section 4 presents the results. Section 5 provides suggestive evidence for the main mechanism and discusses potential alternative explanations. Section 6 concludes.

2 Theoretical Framework and Hypotheses

This section explains the reasoning behind our hypotheses about how performance information may affect workers' beliefs, mental health, and retention, focusing on two mechanisms: social comparison and career concerns.

We consider a workplace with two types of employees: senior workers who have been at the firm for a longer time, and new workers who joined more recently. Worker performance depends on both inherent ability and experience at the firm. For most of this section, we abstract away from effort provision, though we return to it later.

We assume that a worker's utility includes two components: (1) a monetary payoff, which is proportional to performance, and (2) a psychological cost from upward social comparison, which increases with the perceived abilities of high-performing senior coworkers. The assumption of upward social comparison is grounded in our pre-RCT survey, where 58% of workers reported comparing themselves to high-performing colleagues (see Figure A2). The assumption that psychological costs increase with the perceived abilities of referent workers follows prior research showing that upward social comparisons to more capable others often generate envy and stress and lower self-esteem (e.g., Matthews and Kelemen, 2025). The assumption that social comparison focuses primarily on perceived inherent ability is based on prior research on the "naturalness bias," which shows that people tend to admire those who appear naturally talented more than those who achieve success through effort or experience (Tsay, 2016). A worker stays at the firm if her expected utility exceeds a fixed outside option.

New workers observe the current performance of their coworkers but lack information about how senior workers performed earlier in their tenure. This limited information means that new workers may misjudge how much senior coworkers' current high performance is due to experience versus ability. Prior research on the fundamental attribution bias suggests that people tend to over-attribute success to internal factors and under-attribute it to situational ones, such as experience (Ross, 1977). Recent studies also show that people tend to underestimate learning-by-doing (Horn and Loewenstein, 2025). Based on these findings, we assume that new workers overestimate the inherent abilities of high-performing senior coworkers and underestimate the role of experience.

These misperceptions create two key effects:

1. Social comparison: New workers tend to incorrectly believe that high-performing senior coworkers are innately superior, leading to greater psychological costs and worse mental health.

2. Career concerns: A large literature on self-efficacy in learning posits that people form beliefs about their own future performance by observing the experience of others (Bandura, 1997). If new workers believe that their performance growth trajectories will be similar to those of their high-performing senior coworkers, then underestimating the senior workers' returns to experience will also lead to pessimism about their own future prospects.

We hypothesize that providing new workers with performance trajectory information, that is, data on how senior coworkers' performance evolved, helps address both issues. It corrects overestimates of inherent ability, easing the stress of upward comparison. It also corrects underestimates of the value of experience, encouraging more positive expectations about future performance. Together, these effects should increase retention among new workers.

Hypothesis 1. (Effects of Performance Trajectory Information on New Workers)

a (*Turnover*) Performance trajectory information reduces new worker attrition.

b (*Beliefs*) It lowers beliefs about senior coworkers' initial performance.

c (*Social comparison*) This belief revision improves new workers' mental health.

d (*Career concerns*) If new workers believe their learning potential is similar to that of senior coworkers, the information raises expectations about their own future performance.

The causal chain in this hypothesis is illustrated in Figure 2 along with the empirical tests of the links therein.

[INSERT FIGURE 2]

While we have so far assumed that workers' effort is fixed, if effort is instead a choice variable that contributes to performance growth, then career concerns may also shape how much effort workers exert. The direction of this effect, however, is theoretically ambiguous. When effort and experience are complements, higher expected returns to experience should encourage greater effort. In contrast, when they are substitutes—as may occur under reference-dependent preferences—workers who learn that achieving a given performance level is easier than expected may reduce their effort.

In contrast to new workers, we expect that performance information will have little effect on senior workers. By the time they reach this stage, senior workers have already learned about the trajectories of their own and others' performance. As a result, additional performance information is unlikely to change their beliefs, expectations, or mental well-being.

Hypothesis 2. (Effects of Performance Information on Senior Workers) Performance trajectory and peer performance information do not affect senior workers' retention.

Providing new workers with peer performance information—that is, information about how other new workers are currently performing—is unlikely to produce the same effects as performance trajectory information. Prior studies find mixed effects of peer performance disclosure on worker behavior and satisfaction (Mas and Moretti, 2009; Nickerson and Zenger, 2008; Tarakci et al., 2018). Exposure to higher-performing peers can motivate effort through social pressure but can also evoke envy and counterproductive behavior, while exposure to lower-performing peers may boost self-efficacy yet only sometimes induces positive behavioral changes. Heterogeneity in both peer performance and workers' reactions may therefore offset one another, leading to muted overall effects (Gutierrez et al., 2025).

Moreover, for peer performance information to meaningfully affect social-comparison costs, new workers must actually compare themselves to peers at a similar stage. This may not hold in settings where high-performing senior workers dominate attention and upward social comparison is prevalent. Indeed, in our pre-RCT survey, only 25% of respondents reported viewing same-stage peers as their primary comparison targets (Figure A2). Finally, because these peers are also newly hired, their performance largely reflects innate ability rather than accumulated learning, conveying little information about the returns to experience. As a result, recipients of peer performance information are unlikely to update their expectations about their own future job prospects. Taken together, these considerations suggest that peer performance information should not significantly affect new workers' attrition or effort.

Hypothesis 3. (Effects of Peer Performance Information on New Workers) Peer performance information does not affect new workers' retention or effort.

3 Research Design

3.1 The Firm

The company we partnered with for this study is the largest multinational spa chain headquartered in China. As an early pioneer in franchised massage services, the firm operates more than 500 stores across North America, Europe, and East Asia. The company provides a wide range of spa and therapeutic massage services and serves more than five million customers annually. Figure A3 shows photos of the company's spa stores and employees.

Our study focuses on 160 stores distributed across China. Importantly for the experimental design, the stores operate independently, and there is limited communication between geographically separated sites. At the time of the experiment, each store employed an average of 42 workers. The company has five organizational layers: senior executives, regional managers, store managers, middle managers, and workers. Each store is staffed by one store manager, multiple middle managers, and three types of workers, with roughly two-thirds of the workforce consisting of spa workers.[2] Figure A4 illustrates the organizational structure within a store.

Spa workers are responsible for providing therapeutic massage services, maintaining client relationships, and selling prepaid gift cards or personalized service packages. Employees typically work five to six shifts per week, scheduled in advance by store managers. Spa worker compensation consists of a piece rate plus task bonuses and sales commissions. Top-performing senior spa workers can earn up to about ¥20,000 (US$2,800) per month, which is competitive for the service sector. Task bonuses and sales commissions are linear functions of returning customer counts and sales volume, with minor adjustments for attendance.[3] Although workers occasionally assist one another, performance depends largely on personal effort.

Middle managers each supervise a team of 10 to 20 workers and are usually promoted from the pool of spa workers within the store. Workers need to perform well to be eligible for promotion consideration. Similar to many other workplaces, teams typically consist of workers at varied tenure levels, from rookies to highly experienced employees. Managers hold regular group meetings, during which workers share

[2] The remainder are primarily assistant spa workers or professional sales associates.

[3] Spa worker performance is primarily driven by sales ability and customer retention. A key performance metric is called customer pick. When a customer first visits a store, a worker is randomly assigned. If the customer is satisfied with the service, she may request the same worker on subsequent visits. Workers who are picked by customers receive an extra bonus. This variable reflects a worker's ability to retain customers. Workers with high customer picks tend to generate higher sales. The compensation scheme is fully incentive-based and does not involve any relative pay or rank-order-based components.

massage and sales techniques with one another and report on work progress. As a consequence, most workers are only familiar with the current performance of coworkers on their own team.

This firm is comparable to other large firms worldwide in two key respects. First, as is common in frontline service jobs in the United States and Europe, employee attrition is high, exceeding 100 percent annually in the pre-RCT period. Second, attrition is heavily concentrated among new hires: monthly turnover surpasses 20 percent during the first six months. According to interviews with managers, workers who stay beyond six months are regarded as senior and are relatively stable. This pattern is highly consistent with evidence from multiple frontline service settings documented in prior research.[4] Involuntary terminations such as firings are extremely rare. Instead, employee departures are almost entirely voluntary, driven by workers' frustration or unmet expectations. During interviews with the senior management team and fifteen store managers, firm executives expressed concern about excessively high turnover rates, especially among new workers. While some employee turnover is healthy and efficient (Siebert and Zubanov, 2009), persistently high turnover—particularly among new workers—creates substantial costs through short staffing, increased recruitment and onboarding needs, and reduced team morale (Friebel et al., 2023). Together, these concerns motivate our study.

3.2 The Experiment

We conducted a 28-week RCT at 160 stores of the spa chain with over 7,000 spa workers from June 22 to December 31, 2019. The design was registered at the start of the experiment.[5] The 160 stores were assigned into three groups: the performance trajectory group (T1, 40 stores), the peer performance group (T2, 40 stores), and the control group (80 stores). Twice every week, spa workers in the treated stores were sent information on the performance statistics of an anonymous coworker through the firm's workforce management mobile application (app). Workers in T1 received information on the performance trajectories of high-performing senior workers. In the peer performance group (T2), workers received information on the current performance of coworkers with similar tenure. For the control group stores, we did not add to or change any preexisting management practices throughout the experiment. Figure A5 shows the study timeline. We describe the details of the experiment below.

[4]Existing studies show that most employee turnover occurs within the first six months in frontline service contexts, including call centers (e.g., Burks et al., 2015), food and beverage (De Stefano et al., 2019), retail (Friebel et al., 2023), sales (Sandvik et al., 2021), and general services (Lazear et al., 2016).

[5]The RCT registry number is AEARCTR-0004281. The experiment was waived by Stanford IRB for approval.

Treatment and Experiment Implementation. Twice every week during the treatment period, we sent each worker in the performance trajectory group (T1) the performance trajectories of an anonymous high-performing senior worker from her region. All T1 workers within a given region received the same message. The message included the year and month the senior worker joined the firm, the region of her store, and her performance statistics—covering customer picks and sales—in month 1, month 3, month 6, month 12 of tenure, and the month prior to message delivery. The high-performing senior workers whose information was sent each month were selected before the start of that month. Specifically, for each region, we first randomly drew a sample of 15 workers who had been employed for more than 12 months. From this sample, we selected 8 workers, oversampling those with high current performance and excluding those with incomplete or less plausible statistics due to extended leave.[6] These 8 workers constituted the pool from which performance trajectory messages were drawn for that region over the following four-week period. See Figure A6 for an illustration.

In the peer performance group (T2), we divided workers within each region into four tenure-based cohorts: those with less than 3 months of tenure, between 3 and 6 months, between 6 and 12 months, and over one year. Since the firm had 13 regions, this resulted in 52 distinct region-tenure cohorts. Twice each week, we randomly selected one worker from each region-tenure group and anonymously shared her customer pick and sales statistics from the previous month with all workers in the same region-cohort group. The selection excluded workers with less plausible performance statistics due to extended leaves but did not otherwise over- or under-sample based on observables. See Figure A7 for an illustration.

In both treatments, information was delivered to workers' cell phones through the company's workforce management app. Table A1 shows sample messages received by workers in treated stores. During the 28-week treatment period, each worker in treated stores received performance statistics on up to 56 coworkers. Workers in the control group did not receive any performance-related information. Throughout the pre-RCT to the post-RCT period, employees from all stores received routine notices, informational updates, and survey questions from the firm as usual.

At the beginning of each month, we obtained the previous month's performance statistics from the firm's human resources (HR) department and used them to update a panel of workers' performance records from 2017 to 2019. The performance statistics used in our information treatments were generated from

[6] For instance, some workers were on leave during one of the five months from which we extract statistics, leading to incomplete trajectory records. A small proportion of workers were on leave during two-thirds of the month, making their performance statistics less plausible or representative of a normal performance trajectory.

this panel dataset, so they were real and up to date. Remember that the performance information we sent out was anonymous, so it was very unlikely that a worker could recognize the identity of the individual referred to in a message. Guessing would also be difficult given the large number of workers in a region. In fact, we learned through interviews that workers rarely remember exact performance statistics, even those of themselves.

Randomization. We used 23 months of spa store pre-treatment data from July 2017 to May 2019 to generate the randomization plan. We used stratified randomization methods, stratifying on attrition rate (the main dependent variable), store revenue, and store size. The 160 stores were randomized into three RCT arms, with each treatment group containing 40 stores. Table 1 shows that the three groups are balanced across all pre-specified observables. In each row of columns 1–4, we regressed the pre-RCT observables on the two treatment dummies. Column 1 shows the means in the control group stores. Columns 2 and 3 report the differences between each treatment group and the control. Column 4 shows the p-value for the F-statistic testing the joint significance of the two treatment dummies. Neither dummy is statistically significant. Columns 5 and 6 compare the combined treatment groups to the control group, and again, none of the coefficients are statistically significant.

[INSERT TABLE 1]

RCT Validity. Three key considerations support the validity of this field experiment. First, the risk of noncompliance is minimal: all store personnel were required to use the workforce management app during their shifts, and unread messages appeared automatically when the app was opened, ensuring that treated employees were exposed to the information. Second, the potential for a Hawthorne effect is unlikely, as neither workers nor managers were informed about the RCT, and the treatment messages were designed to match the firm's routine communications. Crucially, any residual Hawthorne effects should cancel out across treatment arms given that the two treatment groups received information with similar content and at the same frequency. Third, the intervention delivered a genuine information shock because employees had limited prior exposure to the performance benchmarks introduced by the messages. Senior workers' early stage performance was largely invisible to others due to the transient nature of such data. Historical records are not retained in day-to-day dashboards, nor are they discussed informally. As a result, workers typically observed only the current performance of seasoned employees, not how they progressed over time. Similarly, information about peers at the same tenure level was rarely available. Teams were composed of employees with varying tenure, leaving few coworkers at a similar stage to compare against, and limited cross-team and cross-store interaction further restricted access to peer data.

Data and Measurement. We leverage personnel, accounting, and survey data from the firm to evaluate the effects of trajectory and peer performance information. Our analysis uses six sources of data. First, we have monthly data on the attrition of individual spa workers from June through December 2019. We construct a worker-month panel: attrition is coded as 1 if an employee leaves during a given month and 0 otherwise. The second administrative data set comprises monthly performance measures at both the individual and store levels. For individual-level performance, we use data from June through December 2019. For store-level performance, we use data from January through December 2019. At the individual level, spa workers have four major labor supply and performance measures: the number of days of attendance, customer pick, sales, and compensation. In the spa industry, service workers are usually randomly assigned to new clients. A task is counted as a customer pick when the client is satisfied with the rendered service and selects the same spa worker for future visits. Customer pick thus serves as a good measure of a worker's ability to retain customers. Individual sales are calculated as the sum of pre-paid card and service package sales. Since the compensation scheme includes piece rates, task bonuses, and sales commissions, monthly compensation can be viewed as a measure of overall performance. At the store level, performance is measured by store revenues. Third, data on individual worker demographics (e.g., age, gender, marital status) and stores' administrative information (e.g., number of employees, store size, years of operation, revenue, turnover, location) were collected for July 2017 to December 2019. Fourth, we record detailed implementation data for each piece of information sent to treatment-group workers, including the timing, performance statistics, and recipient of each message.

Fifth, we collect high-frequency employee survey data using the firm's workforce management app. These surveys span the duration of the RCT and cover four dimensions: job satisfaction, evaluation of managers, stress levels, and mental health.[7] For job satisfaction, questions include overall satisfaction, trust, sense of belonging, whether an employee would recommend the company as a place to work, and willingness to stay. Manager evaluation questions capture employee-reported levels of managerial care, problem-solving skills, willingness to seek help from managers, ease of requesting leave, and perceived

[7] We conducted multiple testing before the experiment to check if workers were afraid of expressing themselves and found no such evidence. In survey questions collecting workers' thoughts and critiques about their managers, we received thousands of very detailed comments, some of which were even harsh. When we presented these comments to the firm's Chairman, CEO, and regional managers, they were amazed at the accuracy and authenticity of the responses.

fairness. For mental health, we refer to the Warwick-Edinburgh Mental Wellbeing Scales,[8] covering ten distinct dimensions such as optimism, exhaustion, and curiosity. All survey questions are measured on a 1–5 Likert scale, with higher values indicating greater satisfaction or more favorable evaluations of managers. For ease of interpretation, stress-related items are reverse-coded such that a score of 5 reflects the lowest level of stress. We compute average scores within each dimension and aggregate responses to the worker–month level. Table A2 lists the detailed survey questions by dimension.

Sixth, we also collect survey data on employee beliefs using the firm's workforce management app from June 2019 through January 2020. These belief surveys complement the well-being data described above and cover workers' own sales forecasts, confidence in those forecasts, and perceptions of peer and senior worker performance. In addition, we conduct a one-time post-RCT survey to assess belief revision, changes in perceived performance dynamics, and perceived competitiveness and stress. Tables A3 and A4 list the relevant survey questions. In addition to these data, we interviewed over one hundred spa workers, middle managers, and store managers from 2018 to 2020 and took detailed notes to better understand the mechanisms behind the observed effects.

Econometric Framework. To estimate the treatment effects on individual-level outcomes, we use a single-difference specification. The random assignment of stores to treatment and control groups ensures that post-treatment differences in outcomes can be attributed to the information intervention, assuming the randomization is valid. Specifically, we estimate the following equation:

$$Y_{ijt} = \beta_1 \times T_{1i} + \beta_2 \times T_{2i} + \gamma X_{ijt} + \tau_t + \lambda_r + \delta S_j + \epsilon_{ijt} \tag{1}$$

where Y_{ijt} represents the post-treatment outcome (e.g., attrition, performance, or job satisfaction) for worker i in store j during month t. The treatment indicators T_{1i} and T_{2i} capture the effects of the trajectory and peer treatments, respectively. We include month fixed effects (τ_t) to control for time-specific factors, and region fixed effects (λ_r) to account for unobserved regional characteristics.[9] To further improve estimation precision, we control for individual-level covariates X_{ijt} (such as age, gender, and marital

[8] A brief introduction to the Warwick-Edinburgh Mental Well-being Scales is available on the Warwick Medical School's page.

[9] Store fixed effects are excluded from the model because randomization is done at the store level. Including them would cause the treatment status to be absorbed by the store fixed effects, leading to collinearity between the treatment indicators and the fixed effects. Similarly, individual fixed effects are excluded because each individual within a store is exposed to the same treatment. Therefore, we cannot control for individual or store fixed effects, but we account for these variations using individual- and store-level covariates. Although this approach cannot fully account for unobserved, time-invariant differences across stores, we view it as a necessary tradeoff given the experimental design and structure of the data. While cross-sectional differences across stores might still influence the results, the random assignment of treatment helps mitigate this concern.

status) and store-level characteristics S_j (including whether the store is located in a city, store size, number of workers, and pre-RCT average sales and turnover). The error term ϵ_{ijt} is clustered at the store level. Although our analysis primarily focuses on new workers, who are the main target of the intervention, we also present results for senior workers to provide a point of comparison.

We adopt a single-difference specification rather than a difference-in-differences (DID) model because our primary outcome of interest is the attrition of new workers. Under a DID approach, identification would rely solely on workers employed prior to the intervention. This presents two problems. First, as these pre-intervention workers age into senior status, the effective sample of new workers shrinks over time, placing disproportionate weight on the early months of the intervention and leading to very few observations during the later months. This is particularly problematic because the intervention was designed to unfold over a 28-week period, with effects expected to accumulate in later months. Second, a DID design would exclude employees hired during the intervention, even though they constitute a key population for assessing early-stage responses. The single-difference estimator includes all new workers in the post-treatment period and places equal weight on each post-treatment month. It therefore avoids these limitations and yields a cleaner estimate of treatment effects on early-stage employees, aligning with the structure of the data and the study's core objective.

To estimate the effects of the intervention on store-level outcomes, we use a DID specification that leverages both pre- and post-intervention data. The worker-level specification uses a single-difference approach due to sample composition concerns, which are absent at the store level. By including store fixed effects, the DID model adjusts for time-invariant characteristics specific to each store. Formally, we estimate:

$$Y_{jt} = \beta_1 \cdot T_{1j} + \beta_2 \cdot T_{2j} + \beta_3 \cdot \text{Post}_t + \beta_4 \cdot T_{1j} \times \text{Post}_t + \beta_5 \cdot T_{2j} \times \text{Post}_t + \tau_t + \mu_j + \epsilon_{jt} \quad (2)$$

where Y_{jt} denotes the outcome (e.g., total revenue) for store j in month t, Post_t is an indicator for the post-intervention period, and T_{1j} and T_{2j} are indicators for the two treatment groups. The terms τ_t and μ_j represent month and store fixed effects, respectively. The coefficients β_4 and β_5 capture the average treatment effects on store outcomes for the two treatment arms, comparing treated and control stores before and after the intervention.[10]

[10]We also conduct a single-difference estimation of store-level effects. The results are broadly consistent with the DID estimates and are reported in Tables A5 and A6.

4 Results

4.1 Treatment Effects on Individual Attrition and Performance

Table 2 reports average treatment effects of trajectory and peer performance information on workers' monthly attrition. Columns 1–3 focus on new workers, whereas Columns 4–6 examine senior workers. Column 1 includes region fixed effects only and shows that trajectory information lowers new workers' monthly attrition rate by 2.43 percentage points (SE = 1.11), about 12 percent of the control group mean. Column 2 adds month fixed effects; the estimate remains -2.40 percentage points (SE = 1.10), indicating that seasonality does not drive the result. Column 3 further includes individual and store characteristics, and the estimate is -2.26 percentage points (SE = 1.12). Across these specifications, the coefficients on the peer treatment are close to zero and not statistically significant. For senior workers, neither treatment meaningfully affects attrition (Columns 4–6). Column 7 pools all workers and adds interactions between treatment indicators and a new-worker indicator to test whether treatment effects differ by tenure. In this specification, the interaction between trajectory information and the new-worker indicator is -3.65 percentage points and statistically significant at the 1% level, indicating a larger effect for new workers relative to seniors. Combining this interaction with the main trajectory term implies a net effect for new workers of roughly -2.44 percentage points, which is very close to the estimates in Columns 1–3.[11] Appendix Section A further examines heterogeneous treatment effects on attrition across several individual and store characteristics.

[INSERT TABLE 2]

To explore the dynamic effects of the intervention over time, we plot monthly attrition by treatment arm for new workers. Figure 3 panel (a) compares the new workers' attrition from the trajectory group to the control group and reveals three insights. First, new workers' attrition before the RCT moves closely together across the two groups, providing evidence against differential pre-trends. Second, treatment effects appear immediately after the intervention, indicating a prompt behavioral response. Third, the effects are stable and persistent over time. In contrast, Figure 3 panel (b) shows that attrition in the peer-information group is noisy across months, with small rises and falls and no consistent pattern relative to control. Fi-

[11] See Table A7 for month-by-month headcount flows that clarify the worker–month sample (excluding a small number of workers on maternity or extended sick leave).

nally, Figure A8 shows senior workers' attrition for all three groups moves in parallel before and after the intervention, indicating no discernible treatment effect.

[INSERT FIGURE 3]

The same pattern also appears in our survival analysis. Figure A9 displays Kaplan–Meier survival curves for all new workers across treatment arms, which show cumulative retention over months of tenure. While overall, about 70% of new workers leave within 7 months, retention in the trajectory group is consistently the highest among the three groups, and its advantage widens over time. On the other hand, the peer performance group and the control group exhibit no significant difference in retention.

Taken together, the evidence points to a clear pattern. Showing new workers the performance trajectories of senior coworkers lowers their likelihood of quitting, whereas the peer information treatment leaves attrition essentially unchanged. Among senior workers, neither information treatment has much effect on attrition, so the impact is concentrated in the new-worker cohort. Turning to on-the-job outcomes, Table A8 reports average treatment effects on attendance, customer pick, sales, and compensation; the coefficients are small and statistically indistinguishable from zero, indicating that neither information treatment meaningfully affects individual performance.

4.2 Treatment Effects on Store Performance

To examine whether providing performance information to new workers benefits the firm, we study the treatment effects on overall store revenue. Table 3 reports the average treatment effects on log revenue at the store level, using monthly panel data from January to December 2019. In Column 1, which includes no fixed effects, revenue increases by 6.4% in trajectory stores and declines by 1.3% in peer stores. However, these effects are not statistically significant. Adding month fixed effects and store fixed effects leaves the results virtually unchanged (Columns 2 and 3). Across all three specifications, trajectory tends to outperform peer, and Wald tests comparing the two treatments yield p-values around 0.05–0.06.

[INSERT TABLE 3]

Why don't we see clearer improvements in store revenue, even though the treatment reduces new workers' attrition? Two factors may be at play. First, new workers typically start without regular clients and need time to build relationships and grow their sales. Even if the treatment helps them stay longer and become more productive, the resulting revenue gains may not materialize right away. Second, new workers often represent only a small share of total staff. As a result, even meaningful improvements in their retention or performance may be difficult to detect in overall store revenue. These factors suggest that the true benefits of the information intervention on stores may not be fully reflected in the short-term, average-level estimates of treatment effects.

Because the COVID pandemic started shortly after the end of our treatment period, bringing large disruptions to the firm operations, we are unable to study the potential long-term treatment effects on store revenues. However, we can examine the second factor mentioned above by focusing on stores with a large share of new workers. Table 4 estimates the treatment effects on revenues for stores with above-median shares of new workers at baseline. Remarkably, revenue increases by around 15% for stores in the trajectory treatment group. The effects are statistically significant at the 5% level and do not hinge on whether store and month fixed effects are included. In contrast, the peer treatment continues to have no detectable effect on revenue.[12] The finding that performance trajectory information benefits stores with a larger share of new workers is consistent with the individual-level evidence that the intervention's effects on retention and mental health are also concentrated among new workers.

[INSERT TABLE 4]

The regression estimates of the treatment effects on revenue align with graphical evidence tracking store-level revenue over time. Panels (a) and (b) of Figure 4 plot average monthly revenue for the trajectory and peer treatment groups compared to control. In the full sample, pre-intervention trends are nearly parallel, and no clear post-intervention revenue gap emerges; the trajectory group stays only slightly above control. Panels (c) and (d) focus on stores with above-median shares of new workers. In this group, the trajectory group begins to outperform control stores after the intervention, and the gap steadily widens, suggesting a stronger and more sustained effect on revenue.

[INSERT FIGURE 4]

To further cross-validate the regression estimates of the revenue increase in the trajectory group, in Appendix Section B, we conduct a back-of-the-envelope calculation of attrition costs using internal wage data and operational parameters. Each new worker's departure results in a financial loss equivalent to 21

[12] Tables A5 and A6 show similar results using single-difference specifications.

weeks of wages for a service worker, and when aggregated to the store level, attrition accounts for roughly 9.4% of annual store revenue. This is comparable to the magnitude of the treatment effects estimated in the regressions.

5 Potential Mechanisms

Why does the disclosure of high-performing senior workers' performance trajectories reduce the attrition rates of new workers? As we laid out in the theoretical framework, performance trajectory information can lower new workers' beliefs about their senior coworkers' innate abilities, which can increase their willingness to stay at the firm in two ways. First, the revised beliefs can mitigate new workers' feeling of inferiority when comparing themselves with their senior coworkers, reducing stress and improving mental health, which can ultimately lower attrition (*social comparison channel*). Second, knowing that their coworkers significantly improved their performance during their time in the firm could increase new workers' beliefs about their own returns to experience, encouraging them to stay longer (*career concerns channel*). These causal chains are illustrated in Figure 2. In this section, we formally test these causal chains and find evidence supporting the social comparison channel but not the career concerns channel. In Appendix Section C, we consider several other mechanisms and discuss how they are inconsistent with our evidence.

5.1 Social Comparison

Table 5 reports average treatment effects on employees' psychological wellbeing. In the trajectory group, new workers report lower stress and better mental health: the coefficient on low stress is 0.210 (SE = 0.038) and on mental health is 0.094 (SE = 0.034), on a 1–5 Likert scale, where higher values indicate less stress and better mental health. For senior workers, estimates are near zero and not statistically significant. Job satisfaction and evaluations of managers are unchanged for both groups. In the peer performance group, effects on wellbeing are small and not statistically significant for new and senior workers. Consistent with this contrast, Wald tests of equality across treatments indicate that the trajectory and peer effects differ for new workers on stress ($p < 0.001$) and mental health ($p = 0.008$), with no meaningful differences for other outcomes or groups.

[INSERT TABLE 5]

Table 6 tests whether stress reduction and mental health improvement mediate the effect of performance trajectory information on new workers' attrition. In the baseline model without mediators (Column 1), trajectory information reduces monthly attrition by 2.26 percentage points. Adding stress level as a mediator reduces this coefficient by 43.7%, to -1.27, and it is no longer statistically significant (Column 2). Adding mental health alone reduces it by 16.4%, to -1.89 (Column 3). Including both mediators together reduces it by 48.8%, to -1.15 (Column 4). The mediator estimates have the expected sign: lower stress (higher score) and better mental health are each associated with lower attrition rates. Overall, changes in stress and mental health account for almost one half of the trajectory treatment's effect on attrition, indicating that these channels are important drivers of the retention gains. As a placebo check, Table A9 adds job satisfaction and manager evaluation as mediators, and the trajectory coefficient remains essentially unchanged.

[INSERT TABLE 6]

To examine whether the beneficial effects on stress are associated with downward revisions of new workers' beliefs about senior workers' initial performance, we first look at the treatment effects on these belief revisions using post-RCT survey questions from January 2020.[13] As is shown in Table A10, new workers in the trajectory group report a larger downward belief revision about senior workers' early-stage performance, while the effect is absent for senior workers.

To investigate whether lower beliefs about high-performing senior workers' early-stage performance reduce new workers' stress, we zoom in on the content of the information received by workers in the trajectory treatment. Recall that each piece of information contains a senior worker's performance trajectory across her entire tenure at the firm, from the month she joins the company to the most recent month. Since workers receive two messages per week, we calculate the average first-month performance and the average last-month performance contained in the two messages for a given week, and we study their effects on the stress levels reported the following week by workers who received those messages. Column (1) of Table A11 shows that lower first-month performance of senior coworkers leads new workers to report lower stress subsequently. In contrast, the effect of knowing senior coworkers' recent performance is more muted and insignificant. This result directly supports our theoretical assumption that new workers focus on the innate ability, rather than just the current performance, when comparing themselves to

[13]The survey questions are listed in Table A4.

their high-performing senior coworkers. Moreover, Columns (2) and (3) show that information about a senior worker's starting performance affects new workers' stress levels only when the new workers just had a performance decline. This result also aligns with social comparison theory. Prior research in this literature finds that people who experience recent setbacks are more likely to feel inferior under upward social comparison (Aspinwall and Taylor, 1993). Our result indicates that these people are precisely the ones who are helped the most by performance trajectory information.

The social comparison channel is also evident from worker interviews we conducted after the treatment period concluded. One worker in the trajectory group reflected, "*I had poor performance during the sales campaign last summer. I was so upset with myself, I cried several times after work, and wasn't sure whether I should hold on. The information made me realize that it is alright to have such a performance during my current stage. It was not great, but definitely acceptable. I believe I can overcome the difficulty and gradually become stronger.*" According to another interviewed worker, "*senior workers have been like god since I joined the firm, and it was beyond imagination to surpass them. Now that I know many of them accomplished that step by step, they are also ordinary human beings. My current performance is still much lower than the top worker's in my store, but I have a higher tolerance for myself.*" The sentiment of worker responses, though anecdotal, corroborates the impact of sharing performance trajectory information on reshaping their upward comparison process with coworkers.

5.2 Career Concerns

An alternative mechanism for the effects of our trajectory treatment is career concerns (Holmström, 1999), i.e., performance trajectory information improves new workers' beliefs about their prospects at the company. It could be that the trajectory information makes new workers more optimistic about making progress on productivity. Alternatively, frequently emphasizing performance trajectory may indicate to new workers that the company cares about and will likely invest in their personal growth.

If career concerns is a main mechanism, we should expect new workers in the trajectory treatment to have higher beliefs about their own future performance. In Table A12, we examine the effects of treatments on new workers' forecasts of their own future performance. The results show that across forecast horizons, treatments have no significant effects on forecasts. This is not an artifact of measurement errors in forecasts, because forecasts are significantly associated with attrition (Table A13).

Even though new workers in the trajectory treatment do not have different expectations about their future performance, it could still be that they expect the required effort to achieve that performance to be less. This lower expected cost of effort could be what is keeping the attrition low. If that is true, then we should see lower labor supply and productivity in the trajectory treatment. Again, this conjecture is not borne out in the data. Table A8 shows that new workers' current performance and attendance are not significantly affected by the treatments. Taken together, while we cannot rule out the career concerns channel, we fail to find strong empirical evidence supporting it.

6 Discussion and Conclusion

This study examines whether making the returns to experience more visible can reduce early attrition and improve workplace outcomes. We implemented a 28-week field experiment with more than 7,000 workers at a large multinational service firm, in which employees received regular information about the performance trajectories of high-performing senior coworkers. This trajectory information significantly reduced attrition among new workers by 11–12%, with no detectable effect on senior workers. While the average treatment effect on store revenue was modest, we find that in stores with a higher share of new workers, those still navigating the steep portion of the learning curve, revenue increased by roughly 15%. The reduction in attrition is mediated by reduced stress and improved mental health. These improvements in psychological well-being are in turn driven by new workers' lowered beliefs about the early-stage performance of senior coworkers, which reduced their feeling of inferiority when comparing themselves to these coworkers. In contrast, only providing information about the current performance of coworkers with similar tenure had no meaningful effect on any outcome.

6.1 Contribution

Our study contributes to the literature on organizational learning and knowledge transfer by highlighting a distinct but underexplored driver of workforce development: the visibility of the individual-level experience curve. While prior research has emphasized the value of firm-specific skills, individual experience, and the retention of knowledgeable workers for sustaining organizational performance (e.g., Campbell et al., 2012; Ganco et al., 2015; Starr et al., 2018), we show that how employees perceive the learning process itself, particularly in the early stages of tenure, can meaningfully shape organizational outcomes. Simply making the learning curve visible, through regular exposure to the early performance trajectories of high-performing peers, improves retention, reduces psychological stress, and, in settings with many new workers, translates into measurable gains in firm revenue. These findings suggest that part of the strategic inefficiency in labor allocation stems from missing information about the value of experience: workers may exit too early not because experience lacks value, but because its returns are obscured. In this sense, our results bridge the micro-level psychology of early-stage retention with the macro-level dynamics of capability development.

This experiment highlights an important yet understudied informational friction that amplifies the costs of social comparison in the workplace. While the current performance of senior workers is relatively easy to observe, their past performance is less known. In the absence of such information, it is natural for new workers to benchmark themselves against the current high performance of coworkers with years of accumulated experience, despite it being an unfair comparison. In their seminal work, Nickerson and Zenger (2008) theorize three ways to economize on social comparison costs within firms: pay compression, "technology choice," and corporate scope decisions, where managers divest divisions to restrict the scope for comparison (Feldman et al., 2018). Our experiment fits into the second category and could be understood as a simple job design decision restricting opportunities for employees to make costly comparisons. While both pay compression and corporate divestitures are complicated managerial decisions involving the coordination of numerous stakeholders, our study shows that providing performance trajectory information offers a low-cost and scalable intervention that encourages healthier comparisons and reduces the psychological and behavioral costs associated with upward benchmarking.

The absence of effects from the peer performance information intervention highlights the limits of within-cohort comparisons in shaping new workers' behavior. While prior studies have documented diverse effects of peer performance disclosure ranging from enhanced effort to reduced satisfaction (Mas and Moretti, 2009; Nickerson and Zenger, 2008; Tarakci et al., 2018), such effects appear muted in our setting, where upward comparisons to high-performing seniors dominate and same-stage peers are not salient reference points. This finding suggests that effectively reducing social-comparison costs among new workers requires understanding the comparison processes that already shape their perceptions, so that information interventions can target those specific comparisons. More broadly, it points to the need for social comparison theory to move beyond examining the effects of a given comparison target to also consider what determines target selection—and whether interventions such as information provision can productively reshape these comparison processes.

6.2 Generalizability and Future Research Directions

Although our estimates of the effects of performance trajectory information are obtained in an ideal firm setting with a large sample size, it is still important to consider whether conclusions are likely to generalize to other contexts. Several features of our study are particularly relevant for external validity considerations. First, in our firm of study, the past performance of senior workers is difficult to observe. While this is true for many industries, there are notable exceptions such as academia, where the Curricula Vitae and performance trajectories of senior scholars are largely transparent to junior scholars. Second, in our setting, early-stage performance is informative about workers' ability. However, in organizations where luck heavily influences how workers perform in their early stages, new workers may not be able to figure out the innate ability of senior workers from their past performance. Third, while employees in our setting mostly work independently, making individual performance easy to measure and disclose, performance in more collaborative environments is more reflective of joint efforts and, therefore, less directly attributable to individual workers. All these factors could make the provision of performance trajectory information more difficult and less effective than what we observe.

While providing performance trajectory information alone already generates beneficial effects in our experiment, this kind of information intervention has potential to be even more effective if it is complemented with other career development policies. For example, if along with information about senior workers' early-stage performance, companies also provide actionable advice to new workers on how to achieve high performance step by step, then new workers may not only feel less stressed but also find success more attainable. In other words, even though in our experiment, performance trajectory information did not significantly improve workers' outlook on their future achievement, a more comprehensive career development strategy may well induce this positive expectation change.

Our study takes a first step in demonstrating the power of disclosing performance trajectory information to new workers. Future research can investigate how to tailor this information intervention to other types of work environments and study how it can be incorporated into a more holistic approach to helping workers and organizations realize the returns to experience.

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Figures & Tables

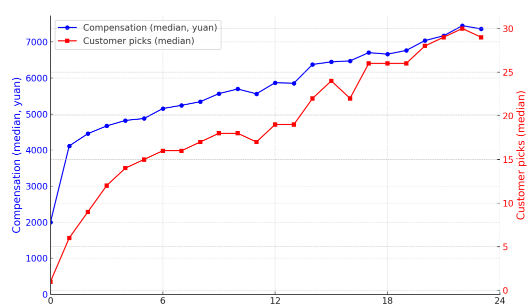


Figure 1: Performance trajectory of experienced workers

Note: This figure presents the trajectory of median customer picks (number of customers who request a specific worker for service) and compensation among experienced workers. The sample comprises all workers employed for at least 12 months and active in June 2019, the month immediately preceding the treatment onset.

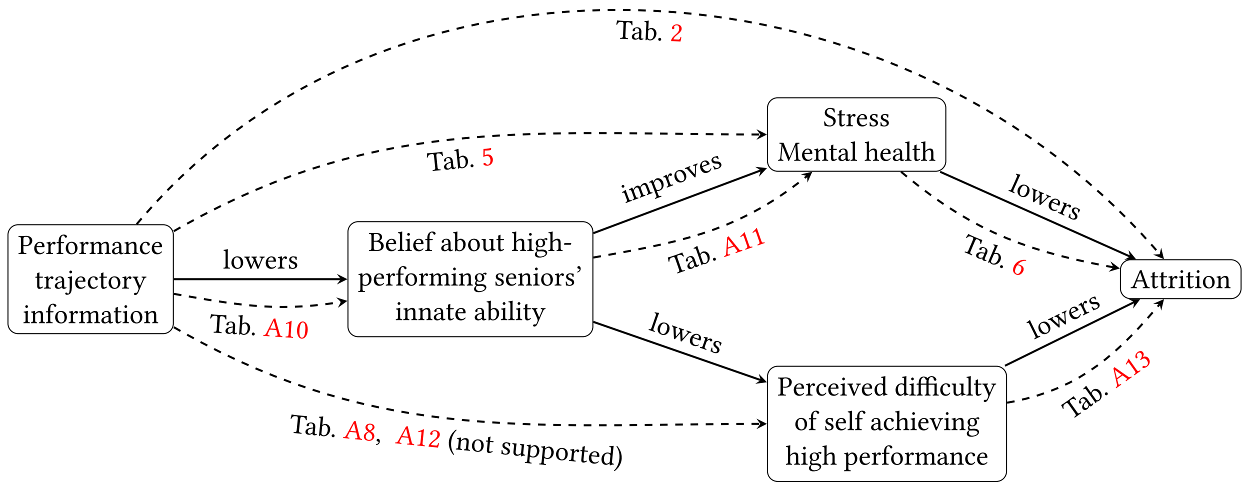
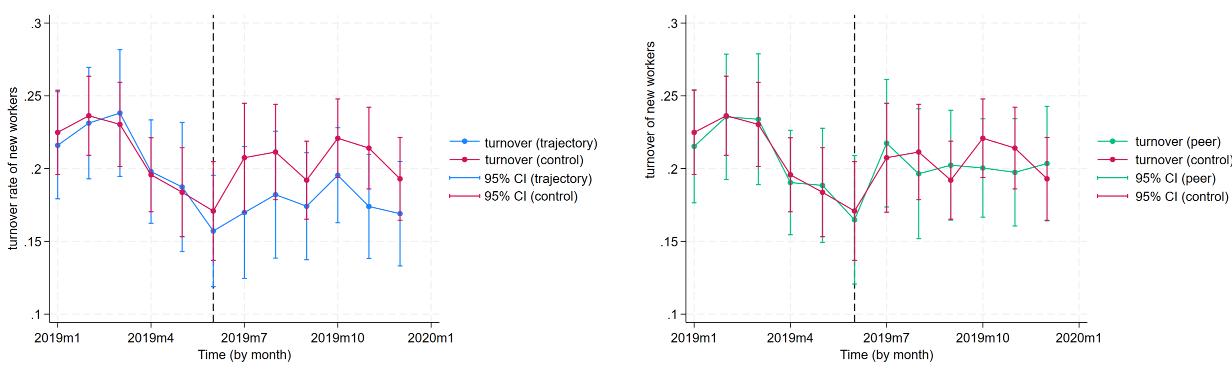


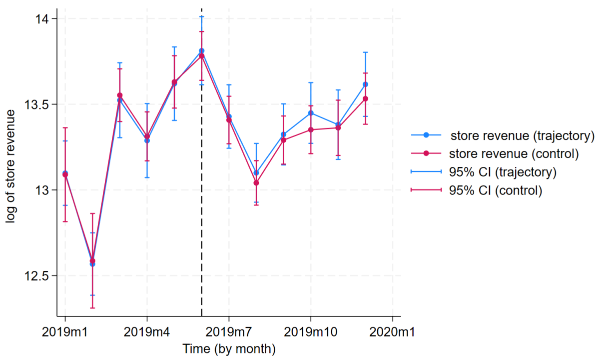
Figure 2: Directed acyclic graph of theorized channels and empirical tests

Note: This figure shows the causal chains for the potential effects of performance trajectory information on new workers' attrition. Solid lines represent hypothesized effects. Dashed lines represent empirical tests.

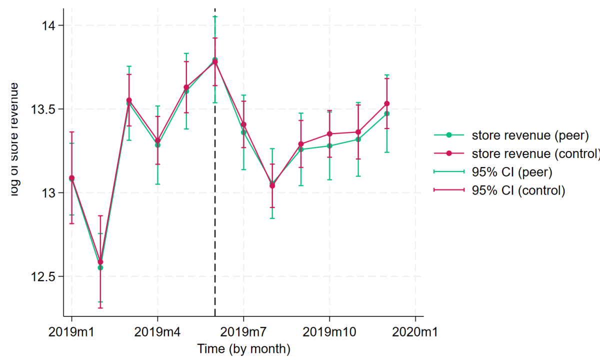


(a) Trajectory vs. Control (Attrition of New Workers) (b) Peer vs. Control (Attrition of New Workers)

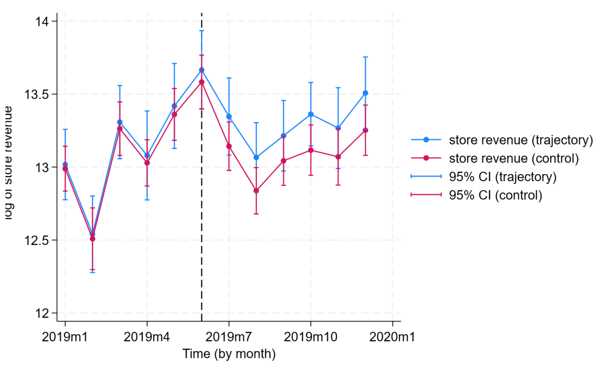
Figure 3: Attrition for new workers.



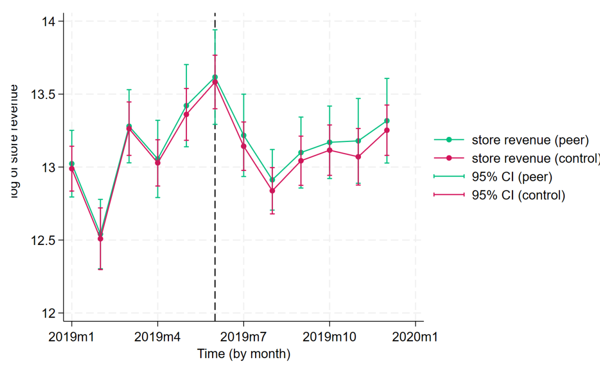
(a) Trajectory vs. Control



(b) Peer vs. Control



(c) Trajectory vs. Control (High New-Worker Share)



(d) Peer vs. Control (High New-Worker Share)

Figure 4: Raw monthly log revenue for treatment and control stores. Top row panels compare trajectory and peer treatments to control. Bottom row restricts to stores with above-median new-worker share at baseline. Points are group means; vertical error bars denote 95% confidence intervals.

Table 1: Comparing Pre-Treatment Store Means across Groups (N=160): Randomization Check

	Comparing All 3 Arms				Treatment vs. Control	
	Control	Trajectory	Peer	p-val	Treatment	p-val
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Store Characteristics						
Revenue in 1000 RMB	646.04	27.75	-16.13	0.94	5.81	0.95
	(62.07)	(107.51)	(107.51)		(87.54)	
Monthly revenue (log)	13.16	0.03	-0.05	0.84	-0.01	0.90
	(0.07)	(0.12)	(0.12)		(0.10)	
Store size (sq meters)	1141.66	-0.29	10.03	0.99	4.87	0.96
	(62.43)	(108.13)	(108.13)		(88.01)	
Store history (years)	4.80	-0.12	-0.09	0.99	-0.10	0.89
	(0.52)	(0.91)	(0.91)		(0.74)	
Monthly turnover	12.87	-0.55	-0.53	0.74	-0.54	0.44
	(0.49)	(0.85)	(0.85)		(0.69)	
Location (city)	0.85	-0.08	-0.08	0.48	-0.08	0.23
	(0.04)	(0.08)	(0.08)		(0.06)	
Panel B. Employee Characteristics						
No. of employees	41.81	2.59	1.01	0.80	1.80	0.57
	(2.21)	(3.84)	(3.84)		(3.12)	
Age	32.58	-0.41	-0.11	0.52	-0.26	0.38
	(0.21)	(0.36)	(0.36)		(0.30)	
No. of spa workers	27.72	0.88	0.33	0.94	0.62	0.77
	(1.50)	(2.57)	(2.62)		(2.11)	
Share male	34.40	2.52	0.47	0.33	1.50	0.28
	(0.98)	(1.70)	(1.70)		(1.39)	
No. of middle managers	2.23	0.08	0.00	0.94	0.04	0.84
	(0.13)	(0.22)	(0.22)		(0.18)	
Store manager male	0.94	0.06	0.01	0.28	0.04	0.25
	(0.02)	(0.04)	(0.04)		(0.03)	

Note: The table compares pre-RCT store-level characteristics across different arms. The pre-RCT period is from July 2017 to May 2019.

Table 2: Average Treatment Effects on Attrition (Linear Probability Models)

	Attrition						
Sample	New Workers			Senior Workers			All Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trajectory	-2.429	-2.397	-2.256	0.917	0.968	1.045	1.218
	(1.110)	(1.099)	(1.120)	(0.805)	(0.783)	(0.704)	(0.744)
	[0.030]	[0.031]	[0.046]	[0.256]	[0.218]	[0.139]	[0.104]
Peer	-0.065	-0.136	-0.207	0.130	0.155	-0.140	-0.090
	(1.276)	(1.263)	(1.160)	(0.870)	(0.840)	(0.710)	(0.740)
	[0.959]	[0.915]	[0.859]	[0.881]	[0.854]	[0.844]	[0.903]
Trajectory × New							-3.654
							(1.353)
							[0.008]
Peer × New							-0.571
							(1.460)
							[0.696]
New							10.036
							(0.881)
							[0.000]
Individual & store controls			✓			✓	✓
Month fixed effects		✓	✓		✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓	✓
Wald p-value (Trajectory = Peer)	0.099	0.110	0.114	0.413	0.382	0.154	0.054
Mean DV if Treatment = 0	20.31	20.31	20.31	9.70	9.70	9.70	12.91
Observations	10,171	10,171	10,171	21,799	21,799	21,798	31,969

Note: Columns 1–7 report results from linear probability models, where the dependent variable is whether an employee quits in a given month. Coefficients are multiplied by 100 for readability. Observations are at the worker–month level and cover the RCT period (June–December 2019). Robust standard errors (in parentheses) are clustered at the store level. p-values are shown in square brackets. Columns 1–3 restrict to new workers, Columns 4–6 restrict to senior workers, and Column 7 pools all workers with interaction terms. Columns 3, 6, and 7 additionally include controls for individual characteristics (age, gender, marital status) and store characteristics (whether the store is located in city, number of workers, area, and pre-RCT average sales and turnover). The Wald p-value tests the null hypothesis of equality between *Trajectory* and *Peer* effects (Columns 1–6) or between the *Trajectory* × *New* and *Peer* × *New* interactions (Column 7).

Table 3: Average Treatment Effects on Store-Level Performance

	log(store revenue)		
	(1)	(2)	(3)
Trajectory × Post	0.064	0.064	0.061
	(0.060)	(0.061)	(0.061)
	[0.287]	[0.295]	[0.319]
Peer × Post	-0.013	-0.010	-0.017
	(0.059)	(0.059)	(0.061)
	[0.823]	[0.869]	[0.776]
Store fixed effects			✓
Month fixed effects		✓	✓
Wald test p-value (Trajectory = Peer)	0.052	0.065	0.059
Mean DV if Treatment = 0	13.33	13.33	13.33
Observations	1,913	1,913	1,913

Note: The table reports the average treatment effects of the information interventions on store-level performance from January–December 2019. Observations are at the store–month level. The dependent variable is log store revenue. Column 1 includes no fixed effects. Column 2 adds month fixed effects. Column 3 includes both month and store fixed effects. Robust standard errors clustered at the store level are shown in parentheses; p-values appear in square brackets. The Wald test row reports the p-value for equality of the *Trajectory* × *Post* and *Peer* × *Post* coefficients.

Table 4: Treatment Effects on Store Revenue: Stores with Above-Median Shares of New Workers

	log(store revenue)		
	(1)	(2)	(3)
Trajectory × Post	0.155	0.155	0.152
	(0.060)	(0.061)	(0.062)
	[0.012]	[0.013]	[0.016]
Peer × Post	0.027	0.033	0.035
	(0.059)	(0.059)	(0.061)
	[0.643]	[0.581]	[0.573]
Store fixed effects			✓
Month fixed effects		✓	✓
Wald test p-value (Trajectory = Peer)	0.024	0.033	0.044
Mean DV if Treatment = 0	13.10	13.10	13.10
Observations	956	956	956

Note: This table reports treatment effects of the information interventions on store-level performance from January to December 2019. The dependent variable is log store revenue, measured at the store–month level. All columns restrict the sample to stores with above-median baseline shares of new workers. Robust standard errors clustered at the store level are shown in parentheses; p-values appear in square brackets. The Wald test row reports the p-value for equality of the *Trajectory* × *Post* and *Peer* × *Post* coefficients.

Table 5: Average Treatment Effects on Individual Survey Outcomes

	Job Satisfaction		Evaluation of Managers		Low Stress		Mental Health	
Worker Sample	New	Senior	New	Senior	New	Senior	New	Senior
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trajectory	-0.021	0.001	-0.029	0.009	0.210	-0.019	0.094	-0.006
	(0.037)	(0.036)	(0.037)	(0.035)	(0.038)	(0.035)	(0.034)	(0.033)
	[0.567]	[0.973]	[0.426]	[0.806]	[0.000]	[0.601]	[0.008]	[0.850]
Peer	-0.042	0.048	-0.028	0.051	-0.023	0.002	-0.023	0.033
	(0.038)	(0.039)	(0.040)	(0.040)	(0.039)	(0.031)	(0.035)	(0.037)
	[0.276]	[0.220]	[0.485]	[0.209]	[0.555]	[0.959]	[0.509]	[0.385]
Individual & store controls	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Wald Test p-val (Trajectory = Peer)	0.674	0.259	0.979	0.270	0.000	0.576	0.008	0.316
Mean DV if Treatment=0	3.98	3.94	4.01	3.88	2.93	2.98	3.76	3.72
Observations	10,171	21,738	10,171	21,798	10,171	21,798	10,171	21,798

Note: This table reports average treatment effects on individual survey outcomes, including job satisfaction, evaluation of managers, stress, and mental health. The original survey questions are summarized in Table A2. All outcomes are measured on a 1–5 Likert scale. The stress measure is reverse-coded so that higher values indicate lower stress. Survey responses are aggregated to the employee–month level, with one observation per worker per month. Regressions include the specified controls for individual characteristics (age, gender, marital status) and store characteristics (city, number of workers, area, and pre-RCT average sales and turnover), and include both region and month fixed effects. Robust standard errors clustered at the store level are reported in parentheses.

Table 6: Mediation Analysis: Effects of Trajectory Information on Attrition (New Workers)

	Attrition			
Mediators	None	Low Stress	Mental Health	Stress + Mental Health
	(1)	(2)	(3)	(4)
Trajectory	-2.256	-1.270	-1.886	-1.154
	(1.120)	(1.132)	(1.121)	(1.133)
	[0.046]	[0.264]	[0.095]	[0.310]
Peer	-0.207	-0.314	-0.299	-0.363
	(1.160)	(1.186)	(1.191)	(1.207)
	[0.859]	[0.792]	[0.802]	[0.764]
Low Stress		-4.705		-3.994
		(0.429)		(0.469)
		[0.000]		[0.000]
Mental Health			-3.957	-2.830
			(0.564)	(0.612)
			[0.000]	[0.000]
Individual & store controls	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓
% Mediated (Trajectory)	–	43.7%	16.4%	48.8%
Observations	10,171	10,171	10,171	10,171

Note: Coefficients are from linear probability models for monthly attrition, multiplied by 100. The stress index is reverse-coded so higher values indicate lower stress. All columns include individual and store controls, and month and region fixed effects. Robust standard errors in parentheses; p-values in square brackets. "% Mediated (Trajectory)" is the percent reduction in the trajectory coefficient relative to the baseline model without mediators.

Online Appendix: Not for publication.

A Heterogeneous Treatment Effects on Attrition

Since we see a significant drop in employee attrition among new workers who have viewed the performance trajectory information, it is natural to examine whether this effect varies with baseline performance. If high-performing workers are more responsive to the trajectory treatment, then the average attrition rate may understate the impact on firm performance due to the retention of exceptional talent. Table A14 conducts a heterogeneous treatment analysis by dividing new workers into high- and low-performing subgroups, using the average monthly productivity over their first three months of tenure, as measured by customer pick.[14]

Table A14 reveals two key patterns. First, baseline performance is a strong predictor of attrition: high-performing new workers in the control group quit much less frequently than low performers (10.5% vs. 32.6%). Second, the effect of the trajectory treatment appears more pronounced among high-performing new workers. Column 2 shows that exposure to performance trajectory information reduces monthly attrition by 1.99 percentage points for high-performing new workers (SE = 0.923), statistically significant at the 5% level. For low-performing workers (Column 1), the estimated effect is smaller (-1.13 p.p.) and imprecise (SE = 2.153). However, the interaction term in the pooled regression (Column 3) is not statistically significant (-1.52 p.p.; SE = 2.863), so we cannot reject the null hypothesis that the treatment effects are equal across the two groups.

We report additional heterogeneous treatment effects across other individual and store level characteristics in Tables A15–A18. Among new workers, trajectory information appears especially effective for female employees and those working in stores with fewer workers. One possible explanation is that men, on average, exhibit greater overconfidence, so performance trajectory information may help female workers update more accurately about their standing, thereby reducing stress. Similarly, stores with fewer workers may offer fewer natural points of comparison, making such information more salient. Across other heterogeneity dimensions (such as age, education, and baseline store turnover), treatment effects are similar in magnitude across subgroups.

[14] The limit of using one's monthly average productivity is that those who stay at the firm for a longer period of time might have higher performance during the later stages of tenure and would thus be more likely to be treated as high-performing workers, which will bias the results. On the other hand, using the performance statistics of each individual month to differentiate high performers from low performers would introduce significant measurement errors especially among new workers. We thus choose the three-month window in order to balance the potential bias and measurement errors. The results are highly consistent using alternative time windows of two or four months.

B The Cost of New-Worker Attrition

We begin by summarizing the wage structure and time commitments relevant to staff departures. Service workers—the core of the frontline workforce—earn about 7,000 RMB per month, while store managers, who oversee recruitment and training, earn about 14,000 RMB per month. We use these wage rates to value the time that managers and workers spend on hiring and onboarding.

Direct costs. Discussions with the Chief Human Resource Officer, the Chief Training Officer, and several store managers indicate that replacing a service worker typically requires 14 working days of the worker's own time and 7 working days of managerial time. Valued at daily wage rates, this amounts to:

$$14 \times \frac{7{,}000}{30} + 7 \times \frac{14{,}000}{30} \approx 6{,}540 \text{ RMB.}$$

In addition, the firm incurs approximately 300 RMB for HR-related tasks—such as processing paperwork, updating payroll systems, and arranging new hire logistics—and another 300 RMB for job advertisements, bringing the total out-of-pocket expense to roughly 7,000 RMB per turnover. To keep the estimate conservative, we exclude legally required benefits and overtime pay that may arise during peak periods.

Indirect costs. We next consider indirect costs. The more significant cost comes from productivity losses during vacancy periods. Although vacancies are posted immediately, managers report that interviews, background checks, and basic training typically take at least two weeks, and a 30-day vacancy is common. A fully trained spa worker generates about 350 RMB in daily gross margin, so a one-month vacancy results in approximately 10,500 RMB in lost revenue.

Replacing a departing worker imposes not only a temporary vacancy but also a sustained productivity loss during the onboarding period. For example, assume that an average new worker resigns at the end of their third month. The replacement must then restart from the beginning of the learning curve rather than continue from where the quitter left off. On average, workers in their first three months complete 64 tasks per month, while those in months four through six complete 82 tasks. If each task yields 100 RMB in gross margin, and workers in months 4–6 generate 4,000 RMB more in monthly sales margin than those in months 1–3, then the monthly performance gap is:

$$(82 - 64) \times 100 + 4{,}000 = 5{,}800 \text{ RMB}.$$

Over three months, this gap results in a total productivity loss of approximately 17,400 RMB.

Departures also affect co-workers. Considering the spillover effects on incumbent workers, we conservatively assign a 1,600 RMB productivity loss to each turnover event. This estimate is based on discussions with store managers and frontline employees, who note that departures require rescheduling shifts and informal coaching of new hires, often causing brief disruptions in workflow and morale.

Total cost. Adding the direct cost (≈7,000 RMB), vacancy loss (≈10,500 RMB), learning curve loss (≈17,400 RMB), and spillover cost (≈1,600 RMB) yields a total cost of approximately 36,500 RMB for each turnover event. To put this in perspective, an average service worker earns about 7,000 RMB per month, or roughly 1,750 RMB per week. The total cost of each turnover event is therefore equivalent to about 21 weeks of pay:

$$\frac{36{,}500}{1{,}750} = 20.9 \approx 21 \text{ weeks}.$$

Contextualizing the estimate. How does this compare to prior estimates? The cost of a turnover event is about 21 weeks of pay, higher than comparable figures from large retail settings—12.5 weeks in Friebel et al. (2023) and 17 weeks in Blatter et al. (2012). Two features likely account for the gap. First, spa services rely on direct, in-person delivery, which limits substitution across staff. Second, spa workers face a longer learning period to master massage techniques and client routines.

Economic significance at the store level. We then translate the cost per turnover event into annual terms for a typical store. We focus on spa workers in their first six months—the group most affected by the intervention. In the control group, their monthly attrition rate is about 20%. Each store typically employs 27 spa workers, and firmwide data indicate that the median store has about 31% new workers. That implies roughly 8.3 new spa workers per store at a given time. Applying the 20% monthly attrition rate implies about 1.66 turnover events per store per month, or roughly 20 per year.

The average cost per turnover event (direct plus indirect) is about 36,500 RMB. Multiplying by 20 events gives an annual attrition cost of about 730,000 RMB per store for new spa workers. For context, average monthly store revenue is approximately 646,040 RMB, or 7.75 million RMB per year. Thus, attrition among new spa workers costs roughly 9.4% of annual store revenue, similar in magnitude to the revenue gains we estimate at the store level.

These calculations rely on conservative assumptions. First, we assume that the proportion of new workers remains constant throughout the year and across stores. Second, we do not account for potential longer-term spillovers, such as lost customer loyalty, damage to brand reputation, loss of upselling opportunities, or reductions in managerial focus on growth and performance management. As a result, the true cost may be higher than our estimate. Even under these conservative assumptions, attrition among new workers imposes a sizable financial burden on the firm.

C Other Mechanisms

We find little support for several alternative mechanisms.

Performance trajectory information may also convey positive signals about the firm or the industry. One possibility is that employees responded to the trajectory treatment because it helped them form broader impressions about the organization. For example, the firm's ability to document and share detailed statistics might lead workers to infer that the organization, or even the industry more generally, is well-organized, data-driven, and therefore a promising place for long-term employment. However, this channel would predict a positive treatment effect on job satisfaction, which we do not find (see Table 5).

Performance trajectory information reassures risk-averse workers. Another potential explanation for our results is that workers feel more anxious about the future when they just start working and face a significant degree of uncertainty. For example, they might have little knowledge of what their performance will look like in, say, six months, and the multiple data points contained in a trajectory message reduce the unpredictability of their future performance and reassure workers who are generally risk-averse. To explore this possibility, we look at how trajectory and peer performance information affect workers' degree of certainty of their predictions of future performance. In Table A19, we see significantly higher certainty among workers who receive peer performance information, whereas the effect on the trajectory group is much smaller and statistically insignificant.[15] The test thus shows suggestive evidence against this

[15] One natural question to ask is why peer information decreases workers' sense of uncertainty more effectively compared to the trajectory information. Our interpretation is that workers have performance more similar to that of coworkers with similar tenure. Viewing the current performance of peers could give workers a more precise idea of what their performance would look like in the near future. In contrast, the trajectory information of senior workers contains two additional sources of noise. First,

explanation.

Performance trajectory information lowers risk-averse workers' belief about variation in performance over time. One possible explanation is that trajectory information helps workers realize their performance is likely to be more stable than they had expected, reducing uncertainty and encouraging them to stay. Table A20 shows the treatment effects on new workers' self-perceived performance fluctuation. The estimates are small and statistically insignificant, and the coefficients for both peer and trajectory treatments are similar in magnitude, suggesting that this mechanism is unlikely.

Trajectory information and competitiveness. Another possibility is that, after seeing the performance trajectories of star employees, workers become more motivated to stay and compete. However, Table A20 shows that while trajectory information has a marginally significant effect on competitiveness among senior workers, its effect on new workers is limited. This suggests that increased competitiveness is unlikely to be the main channel driving retention among new workers.

significant selection effects apply to senior workers, as only high-performing workers tend to stay. If the new worker is a low type, it would be extremely noisy to infer their future performance based on the senior worker's trajectory. The second source of noise is time fixed effects. New workers need to tease out both effects from the trajectory information, which reduces their certainty about the estimate's accuracy.

D Additional Figures and Tables

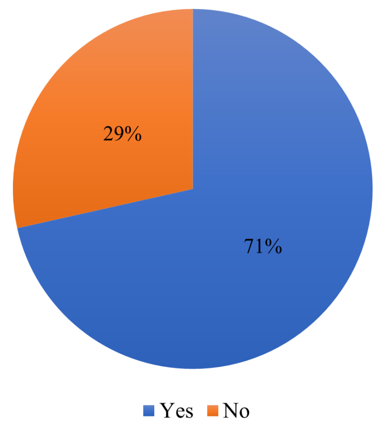


Figure A1: More than 71% of 3,470 surveyed spa workers often compare their performance to that of their coworkers.

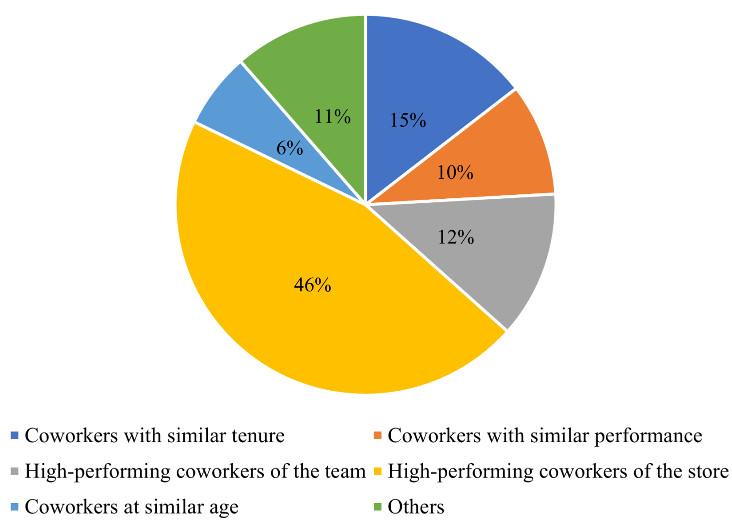


Figure A2: More than 58% of the surveyed spa workers often compare their performance to high-performing coworkers of their team or store.

(a) Store lobby

(b) Spa room

(c) Service

(d) Speech to store managers during corporate annual conference

Figure A3: The company is the largest multinational spa chain, headquartered in China, with more than 500 stores worldwide.

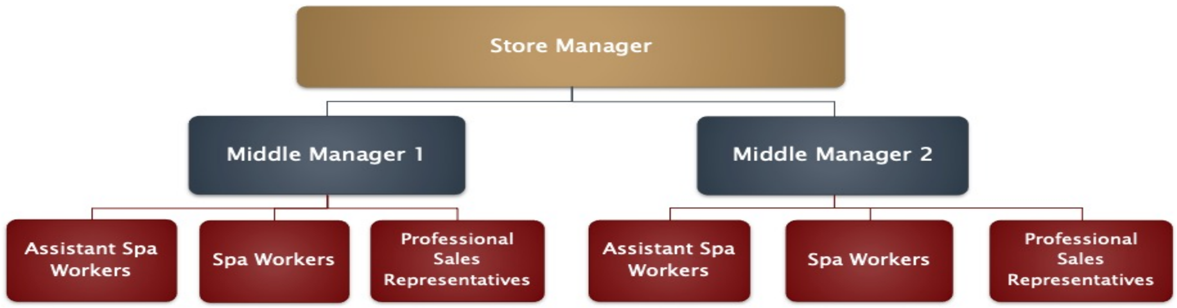


Figure A4: Organizational chart within a store

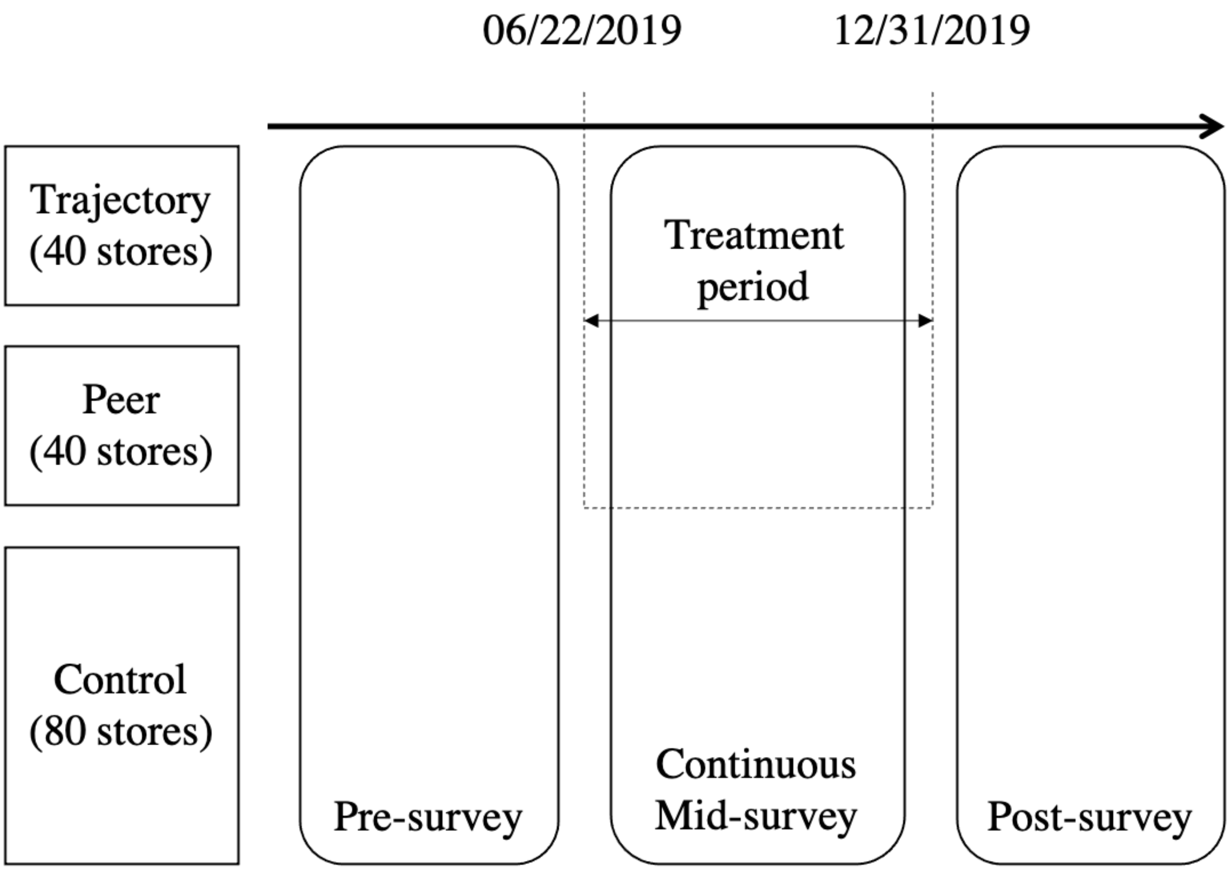


Figure A5: RCT timeline

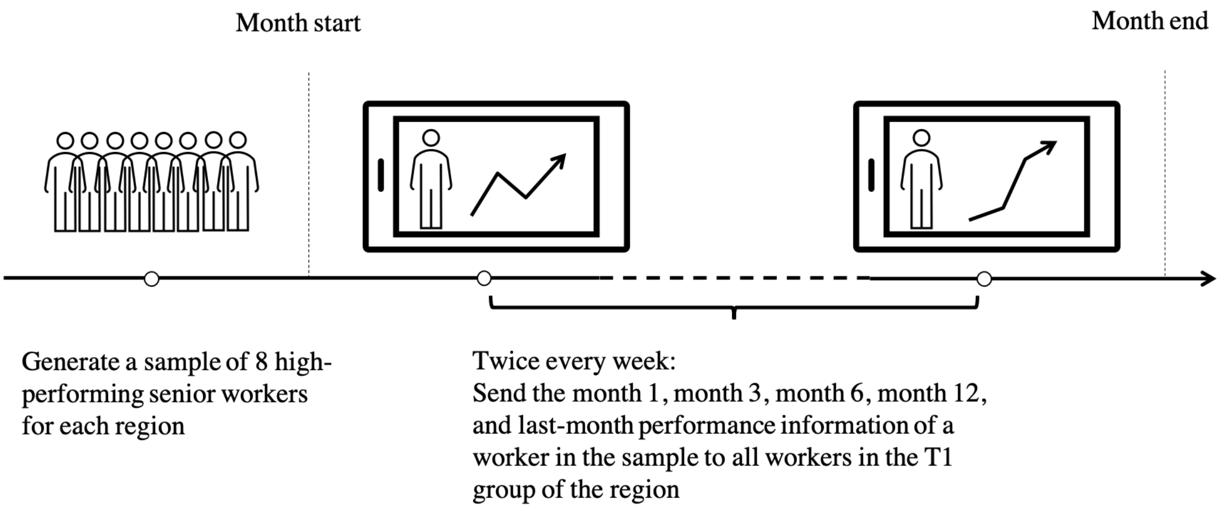


Figure A6: Performance trajectory treatment

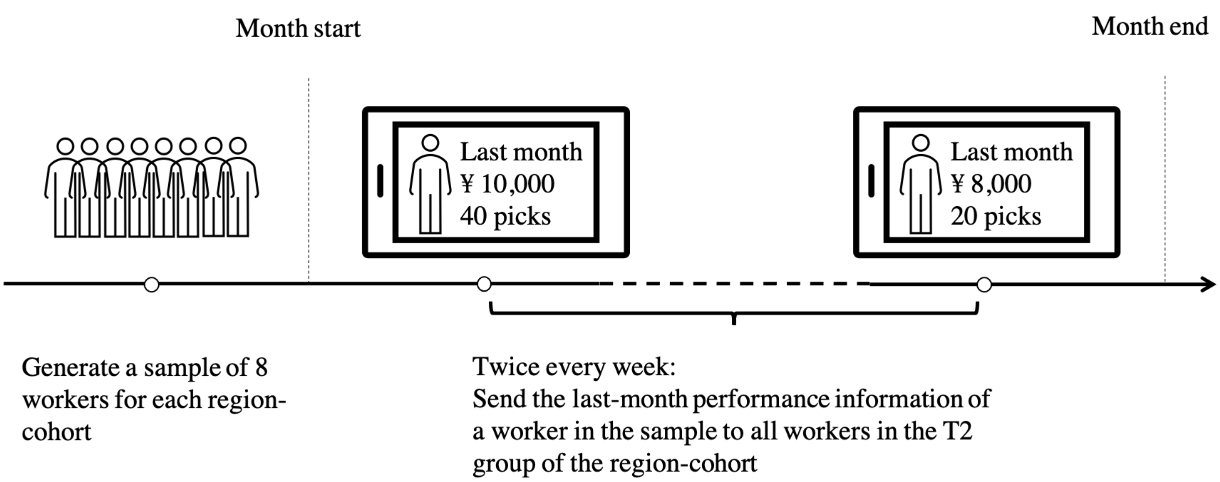
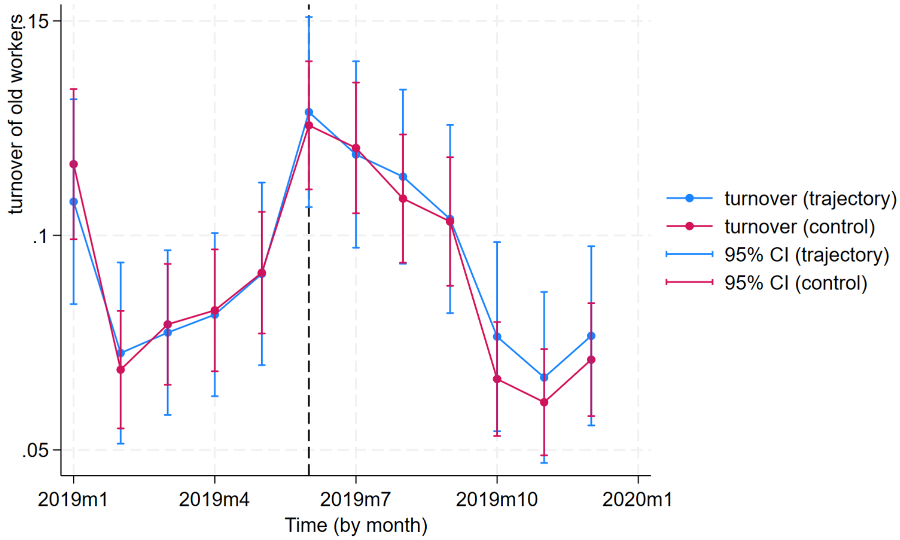
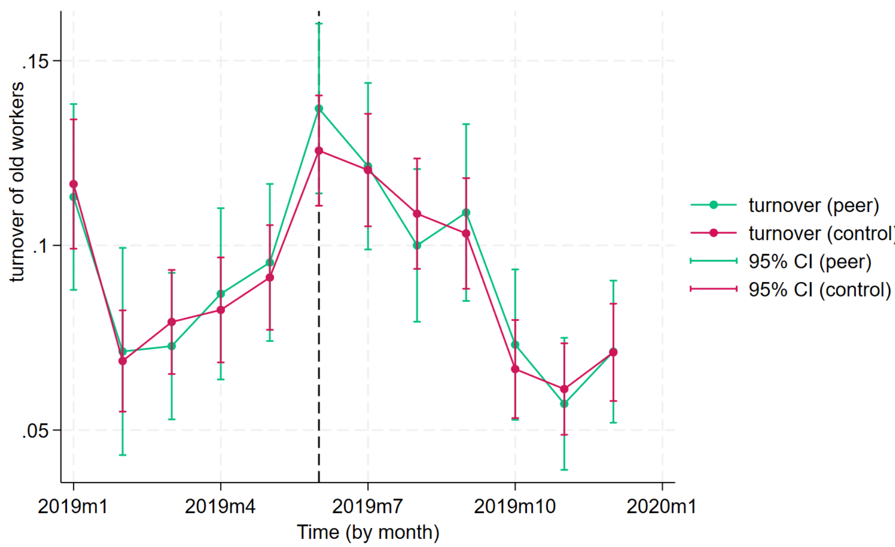


Figure A7: Peer performance treatment

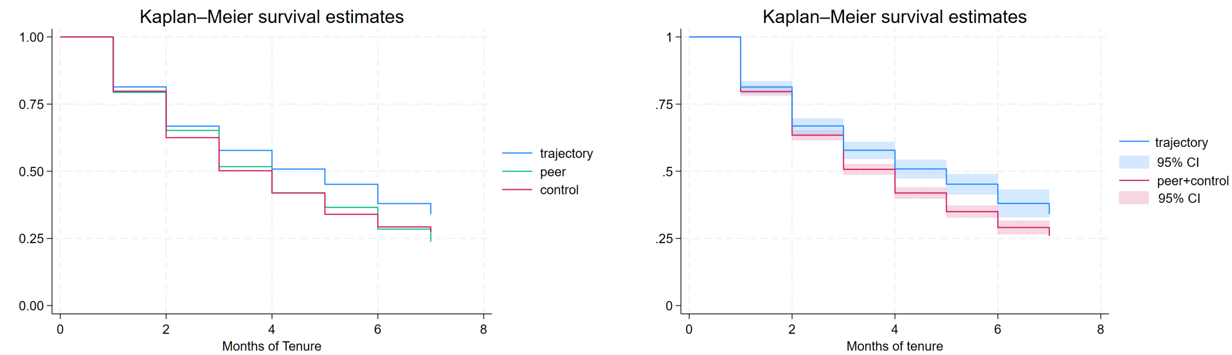


(a) Trajectory vs. Control (Attrition of Old Workers)



(b) Peer vs. Control (Attrition of Old Workers)

Figure A8: Attrition for old workers. Panel (a) compares the raw attrition rates for old workers, trajectory versus control. Panel (b) compares the raw attrition rates for old workers, peer versus control.



(a) Survival of New Workers by Group

(b) Trajectory vs. Other (Survival of New Workers)

Figure A9: Survival Curve Comparisons. Panels (a) and (b) present the cumulative survival probabilities of new workers using Kaplan Meier curves. Panel (a) shows retention by treatment arm (control, trajectory, peer). Panel (b) compares the trajectory group with the combined peer and control groups. Each worker's Month 1 corresponds to her first observed payroll month during the RCT, regardless of when she was hired.

Treatment Group	Sample Message
Trajectory	In order to promote mutual understanding among [the company]'s employees, today we introduce you to the performance trajectory of Xiaomei (alias). Xiaomei joined [the company] in [region] in [year and month]. In [his/her] first month at [the company], [his/her] customer pick number was [number], [his/her] sales was [number]. * In [his/her] 3rd month, [his/her] customer pick number was [number], [his/her] sales was [number]. * In [his/her] 6th month, [his/her] customer pick number was [number], [his/her] sales was [number]. * In [his/her] 12th month, [his/her] customer pick number was [number], [his/her] sales was [number]. * Last month, [his/her] customer pick number was [number], [his/her] sales was [number].
Peer	In order to promote mutual understanding among [the company]'s employees, today we introduce you to the performance of Xiaomei (alias). Xiaomei joined [the company] in [region] in [year and month]. Last month, [his/her] customer pick number was [number], [his/her] sales was [number].

Table A1: Sample messages to spa workers of the two treatment groups

Category	Dimension	Sample Questions
Job Satisfaction	Satisfaction	How satisfied are you with your job in the company?
	Trust	How much trust do you have for the company?
	Sense of belonging	How much sense of belonging do you have for your job and the company?
	Recommendation	Have you suggested or helped family or friends get a job at the company?
	Staying	Are you willing to stay in the company for long?
Manager Evaluation	Care	Do your managers talk to/care about you?
	Problem-solving	Are managers capable of resolving problems when you need them?
	Willing to turn to	If you have troubles, how willing are you to reach out to your manager for help?
	Leave	If you ask for leave when it is really necessary, how easy is it for you to get approval from your manager?
	Fairness	How fair do you think your manager is?
Stress	Stress	How much stress do you feel on the job?
Mental Health	Optimism	I've been feeling optimistic about the future.
	Useful	I've been feeling useful.
	Relaxed	I've been feeling relaxed.
	Energy	I've been feeling interested in other people and have energy to spare.
	Problem-solving	I've been dealing with problems well.
	Self-feeling	I've been feeling good about myself.
	Closeness	I've been feeling close to other people.
	Being loved	I've been feeling loved.
	Curiosity	I've been interested in new things.
	Cheerful	I've been feeling cheerful.

Table A2: Recurring survey questions on job satisfaction and well-being during the RCT

Note: All questions use a 1–5 Likert scale. Higher scores indicate more satisfaction, more favorable evaluation of manager, lower stress, and better mental health.

Category	Sample Questions
Forecast on next month's sales	What is your forecast of your sales in July?
	How confident are you about your forecast?
Forecast on sales in three months	What is your forecast of your sales in September?
	How confident are you about your forecast?
Belief about average sales of peers in the last months	What is your estimate of the average June sales of your peers (whose start dates at the company are within two months from yours) in the same region?
	How confident are you about your estimate?
Belief about senior workers' early performance	Some workers in your region joined the company last July. What is your estimate of their average sales last September?
	How confident are you about your estimate?

Table A3: Recurring survey questions on beliefs during the RCT

Category	Questions
Belief about senior workers' early performance	Compared to your belief half a year ago, the actual performance of senior workers (from the same region) in their early tenure stage is: (1 = much lower, 2 = lower, 3 = roughly the same, 4 = higher, 5 = much higher).
Belief about peer workers' performance	Compared to your belief half a year ago, the actual performance of workers with similar tenure (from the same region) is: (1 = much lower, 2 = lower, 3 = roughly the same, 4 = higher, 5 = much higher).
Belief about sales fluctuation	Compared to your belief half a year ago, the month-to-month performance fluctuations among colleagues in your region is: (1 = much smaller, 2 = smaller, 3 = roughly the same, 4 = bigger, 5 = much bigger).
Perceived competitiveness	Compared to half a year ago, your sense of competitiveness is: (1 = much smaller, 2 = smaller, 3 = roughly the same, 4 = larger, 5 = much larger).
Self-perceived stress	Compared to half a year ago, your overall stress level is: (1 = much higher, 2 = higher, 3 = roughly the same, 4 = lower, 5 = much lower).

Table A4: One-time post-RCT survey questions on belief revision and social comparison

Table A5: Average Treatment Effects on Store Revenue: Single-Difference Specification

	log(store revenue)		
	(1)	(2)	(3)
Trajectory	0.049	0.049	0.078
	(0.105)	(0.106)	(0.088)
Peer	-0.033	-0.033	-0.053
	(0.089)	(0.088)	(0.089)
Region fixed effects			✓
Month fixed effects		✓	✓
Wald test p-value (Trajectory = Peer)	0.594	0.596	0.378
Observations	1,117	1,117	1,117

Note: Estimates use only post-RCT observations (June–December 2019). Each column reports coefficients from a linear regression of log store revenue on treatment indicators. Column 1 includes no fixed effects. Column 2 adds month fixed effects. Column 3 adds month and region fixed effects. Robust standard errors clustered at the store level are shown in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A6: Treatment Effects on Store Revenue: High New-Worker Share Stores (Single Diff. Spec.)

	log(store revenue)		
	(1)	(2)	(3)
Trajectory	0.198*	0.198*	0.186*
	(0.109)	(0.110)	(0.098)
Peer	0.067	0.067	-0.091
	(0.103)	(0.104)	(0.111)
Region fixed effects			✓
Month fixed effects		✓	✓
Wald test p-value (Trajectory = Peer)	0.283	0.286	0.094
Observations	560	560	560

Note: Estimated using only post-RCT observations (June–December 2019) for stores with above-median baseline shares of new workers. The dependent variable is log store revenue at the store–month level. Column 1 includes no fixed effects. Column 2 adds month fixed effects. Column 3 adds month and region fixed effects. Robust standard errors clustered at the store level are shown in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A7: Monthly Head-Count Flows, July–December 2019

Month	Workers at start	New hires	Exits	Workers at end
July 2019	4,100	486	586	4,000
August 2019	4,000	571	556	4,015
September 2019	4,015	585	539	4,061
October 2019	4,061	479	455	4,085
November 2019	4,085	433	425	4,093
December 2019	4,093	371	446	4,018

Note: A small number of service workers on maternity or extended sick leave are not included in these head-count figures.

Table A8: Average Treatment Effects on Individual Labor Supply and Performance

	Attendance		Customer Pick		log (sales)		log (compensation)	
Worker Sample	New	Senior	New	Senior	New	Senior	New	Senior
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trajectory	0.714	-0.343	0.429	0.664	0.020	0.012	0.021	-0.012
	(0.477)	(0.360)	(1.857)	(2.112)	(0.057)	(0.047)	(0.032)	(0.026)
Peer	-0.215	-0.152	-0.630	-1.982	0.004	-0.042	-0.018	-0.027
	(0.406)	(0.359)	(1.538)	(1.875)	(0.062)	(0.046)	(0.034)	(0.023)
Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Wald Test p-val (Trajectory = Peer)	0.095	0.670	0.584	0.233	0.827	0.338	0.344	0.650
Mean DV if Treatment=0	22.17	25.68	17.16	42.58	9.43	9.91	8.71	9.12
Observations	10,160	21,744	9,977	20,933	10,140	21,360	10,170	21,787

Note: Observations are at the worker-month level and cover the RCT period (June to December 2019). All regressions include controls for individual characteristics (age, gender, marital status) and store characteristics (city, number of workers, area, and pre-RCT average sales and turnover), as well as month and region fixed effects. Robust standard errors clustered at the store level are in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A9: Additional Mediation Analysis: Effects of Trajectory Information on Attrition (New Workers)

	Attrition		
Mediators	None	Job Satisfaction	Eval. of Managers
	(1)	(2)	(3)
Trajectory	-2.256**	-2.318**	-2.317**
	(1.120)	(1.116)	(1.128)
Peer	-0.207	-0.329	-0.265
	(1.160)	(1.177)	(1.175)
Job Satisfaction		-2.946***	
		(0.608)	
Eval. of Managers			-2.069***
			(0.577)
Individual & store controls	✓	✓	✓
Month fixed effects	✓	✓	✓
Region fixed effects	✓	✓	✓
% Mediated (Trajectory)	–	–	–
Observations	10,171	10,171	10,171

Note: Coefficients are from linear probability models for monthly attrition, multiplied by 100. All columns control for the specified individual and store characteristics, and include region fixed effects. Robust standard errors in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A10: Treatment Effects on Beliefs about Senior Workers' Early-career Performance

	Beliefs about Senior Workers' Early-career Performance	
Worker Sample	New	Senior
	(1)	(2)
Trajectory	-0.234**	0.054
	(0.094)	(0.054)
Peer	0.133	0.066
	(0.114)	(0.060)
Region fixed effects	✓	✓
Mean DV if Treatment = 0	3.51	3.40
Wald test p-value (Traj. = Peer)	0.008	0.833
Observations	999	1,938

Note: The table reports treatment effects on workers' self-reported beliefs about senior workers' early-career performance using post-RCT survey data. Responses are recorded on a 5-point Likert scale ranging from "1=much lower" to "5=much higher." The original survey question is listed in Table A4. Both columns control for the specified individual and store characteristics and include region fixed effects. Robust standard errors clustered at the store level are in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A11: The Effect of Coworkers' Performance Trajectory Information on Stress of New Workers

	Low Stress		
New Worker Recent Performance	All	Bad Month	Good Month
	(1)	(2)	(3)
Coworkers' performance in the 1st month	-0.521**	-1.072***	-0.125
	(0.251)	(0.344)	(0.269)
Coworkers' performance in the last month	0.0886	-0.0114	0.207
	(0.134)	(0.219)	(0.141)
lagged (Stress Score)	0.294***	0.261***	0.317***
	(0.0197)	(0.0237)	(0.0253)
Store fixed effects	✓	✓	✓
Observations	5,576	2,595	2,981

Note: The table shows the effect of senior workers' performance trajectory information on new workers' stress levels. The performance measure is the number of customer picks (divided by 100) that a worker has in a month. A new worker is classified as having a bad month if her number of customer picks in the current month is lower than the previous month. Otherwise, she is classified as having a good month. Observations are at the worker-week level. All columns include the specified individual controls and store fixed effects. Robust standard errors are clustered at the store level in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A12: Average Treatment Effects on New Workers' Forecasts on Own Future Performance

	log (forecast on next month's sales)	log (forecast on sales in three months)
	(1)	(2)
Trajectory	0.153	0.0473
	(0.0976)	(0.0766)
Peer	-0.125	-0.128
	(0.0913)	(0.0806)
log (sales)	0.419***	0.332***
	(0.0289)	(0.0241)
Month fixed effects	✓	✓
Region fixed effects	✓	✓
Observations	3,023	3,088

Note: The table shows the average treatment effects on individual-level performance forecasts. Observations are at the worker-month level. Both columns include the specified individual and store controls, and month and region fixed effects. Robust standard errors are clustered at the store level in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A13: Correlation between Individual Performance Forecasts and Attrition

	Attrition	
Worker Sample	New	Senior
log (forecast of next month's sales)	-2.13**	0.156
	(0.909)	(0.582)
log (forecast of sales in three months)	1.13	-0.902*
	(1.17)	(0.536)
log (sales)	-1.74*	-1.26***
	(1.03)	(0.343)
Month fixed effects	✓	✓
Region fixed effects	✓	✓
Observations	1,508	4,583

Note: The table regresses attrition on workers' forecasts of future performance and current sales using data from June to December 2019. The coefficients are multiplied by 100 for readability. Observations are at the worker-month level. Both columns include the specified individual and store controls, and month and region fixed effects. Robust standard errors are clustered at the store level in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A14: Do High-performing Employees Stay? (New Workers)

	Attrition		
Sample	Low-performing	High-performing	All
	(1)	(2)	(3)
Trajectory	-1.134	-1.993**	-0.958
	(2.153)	(0.923)	(2.317)
Peer	-0.697	0.270	-1.286
	(2.226)	(1.006)	(2.262)
Trajectory × High-performing			-1.519
			(2.863)
Peer × High-performing			1.834
			(2.607)
High-performing			-26.257***
			(1.796)
Month fixed effects	✓	✓	✓
Region fixed effects	✓	✓	✓
Wald test p-value (Trajectory = Peer)	0.863	0.062	0.272
Mean DV if Treatment = 0	32.63	10.50	19.31
Number of observations	4,049	6,122	10,171

Note: Columns 1–2 estimate treatment effects separately for low- and high-performing new workers, classified using average monthly productivity over their first three months of tenure (measured by customer pick). Workers above the median are defined as high-performing. Column 3 pools all new workers and includes interaction terms between treatment indicators and a high-performance dummy. Coefficients are multiplied by 100; robust standard errors clustered at the store level are in parentheses. All regressions include the specified individual and store controls, as well as region and month fixed effects. The Wald test p-value in Column 3 evaluates the null hypothesis that *Trajectory* × *High-performing* equals *Peer* × *High-performing*. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A15: Heterogeneous Treatment Effects on Attrition (New Workers)

	Attrition					
Worker Sample	Female	Male	Younger	Older	Less Educated	More Educated
	(1)	(2)	(3)	(4)	(5)	(6)
Trajectory	-2.814**	-1.025	-2.195	-2.073	-1.928	-2.759
	(1.314)	(1.814)	(1.432)	(1.582)	(1.427)	(1.746)
Peer	-0.275	0.163	-0.353	0.552	0.788	-1.088
	(1.376)	(2.174)	(1.492)	(1.815)	(1.605)	(1.806)
Month fixed effects	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓
Wald test p-value (Traj. = Peer)	0.123	0.586	0.281	0.192	0.118	0.409
Mean DV if Treatment=0	20.50	19.73	20.49	20.14	19.54	21.39
Observations	7,602	2,569	5,089	5,082	5,790	4,381

Note: Columns 1–6 are linear probability models. The dependent variable is whether an employee quits in a given month. Coefficients are multiplied by 100. Observations are at the worker-month level. All regressions (June–December 2019) include region and month fixed effects and a standard set of controls described in the main text. Robust standard errors are clustered at the store level. ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$)

Table A16: Heterogeneous Treatment Effects on Attrition (Senior Workers)

	Attrition					
Worker Sample	Female	Male	Younger	Older	Less Educated	More Educated
	(1)	(2)	(3)	(4)	(5)	(6)
Trajectory	0.750	1.299	0.873	1.028	1.517*	0.108
	(0.782)	(1.351)	(1.200)	(0.770)	(0.909)	(1.044)
Peer	-0.166	0.050	0.282	-0.575	-0.458	0.248
	(0.840)	(1.258)	(1.204)	(0.802)	(0.820)	(1.184)
Month fixed effects	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓
Wald test p-value (Traj.=Peer)	0.331	0.414	0.691	0.077	0.052	0.915
Mean DV if Treatment = 0	9.81	9.31	11.40	8.36	9.26	10.39
Observations	16,727	5,071	9,875	11,923	13,073	8,725

Note: Columns 1–6 are linear probability models. The dependent variable is whether an employee quits in a given month. Coefficients are multiplied by 100. Observations are at the worker-month level. All regressions (June–December 2019) include region and month fixed effects and a standard set of controls described in the main text. Robust standard errors are clustered at the store level. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A17: Heterogeneous Treatment Effects by Store-level Characteristics on Attrition (New Workers)

	Attrition					
Sample	Town	Big City	Fewer Workers	More Workers	Low Turnover	High Turnover
	(1)	(2)	(3)	(4)	(5)	(6)
Trajectory	0.014	-2.263*	-3.570**	-0.940	-2.057	-2.761*
	(2.136)	(1.290)	(1.463)	(1.500)	(1.418)	(1.639)
Peer	1.330	0.008	1.674	-1.067	-1.793	1.831
	(2.383)	(1.459)	(1.886)	(1.458)	(1.446)	(1.999)
Month fixed effects	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓
Wald test p-value (Traj. = Peer)	0.571	0.170	0.003	0.944	0.855	0.051
Mean DV if Treatment = 0	17.05	20.72	21.52	19.06	20.18	20.41
Observations	1,620	8,551	4,536	5,635	4,615	5,556

Note: Columns 1–6 are linear probability models. The dependent variable is whether an employee quits in a given month. Coefficients are multiplied by 100. Observations are at the worker-month level. All regressions (June–December 2019) include region and month fixed effects and a standard set of controls described in the main text. Robust standard errors are clustered at the store level. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A18: Heterogeneous Treatment Effects by Store-Level Characteristics on Attrition (Senior Workers)

	Attrition					
Sample	Town	Big City	Fewer Workers	More Workers	Low Turnover	High Turnover
	(1)	(2)	(3)	(4)	(5)	(6)
Trajectory	2.25	0.32	0.556	1.034	0.94	0.70
	(1.45)	(0.86)	(1.36)	(0.84)	(0.85)	(1.42)
Peer	1.42	-0.66	-1.149	0.707	0.41	0.11
	(1.46)	(0.92)	(1.20)	(0.99)	(1.01)	(1.38)
Month fixed effects	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓
Wald test p-value (Traj.=Peer)	0.596	0.353	0.271	0.762	0.588	0.722
Mean DV if Treatment=0	9.34	9.76	11.50	8.52	8.74	10.94
Observations	3,946	17,852	7,794	14,004	13,001	8,797

Note: Columns 1–6 are linear probability models. The dependent variable is whether an employee quits in a given month. Coefficients are multiplied by 100. Observations are at the worker month level. All regressions (June–December 2019) include region and month fixed effects and a standard set of controls described in the main text. Robust standard errors are clustered at the store level. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A19: Treatment Effects on Certainty of Self-Predicted Performance

	Certainty of Predictions		
Worker Sample	New	Senior	All
	(1)	(2)	(3)
Trajectory	0.090	-0.001	0.030
	(0.056)	(0.048)	(0.041)
Peer	0.190***	0.014	0.076
	(0.063)	(0.055)	(0.046)
Month fixed effects	✓	✓	✓
Region fixed effects	✓	✓	✓
Observations	5,478	10,349	15,827

Note: The table reports treatment effects on workers' stated certainty about their own sales forecasts three months ahead, using survey data from June–December 2019. After reporting a forecast, workers rated their confidence on a 1–5 scale (higher = more certain); the original survey wording appears in Table A3. All regressions include the specified individual and store controls, and month and region fixed effects. Robust standard errors clustered at the store level are in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table A20: Treatment Effects on Self-Perceived Performance Fluctuation and Competitiveness

	Perceived Volatility		Competitiveness	
Worker Sample	New	Senior	New	Senior
	(1)	(2)	(3)	(4)
Trajectory	-0.036	-0.015	0.077	0.121*
	(0.075)	(0.049)	(0.090)	(0.061)
Peer	-0.041	0.089*	-0.101	-0.089
	(0.086)	(0.054)	(0.104)	(0.073)
Region fixed effects	✓	✓	✓	✓
Mean DV if Treatment=0	3.52	3.31	4.00	3.76
Observations	984	1,946	916	1,751

Note: The table reports treatment effects on workers' self-perceived fluctuation of performance and competitiveness using post-RCT survey data. Respondents were asked to evaluate, relative to half a year ago, (i) the perceived variability in colleagues' month-to-month performance and (ii) their own level of competitiveness, on a 1–5 Likert scale. Higher values indicate greater perceived fluctuation and higher competitiveness. The original survey questions are reported in Table A4. All regressions include the specified individual and store controls, and region fixed effects. Robust standard errors clustered at the store level are in parentheses. (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)