Managerial Attention, Employee Attrition, and Productivity: Evidence from a Field Experiment*

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Abstract

What is the causal impact of managerial attention on employee attrition, productivity, and well-being? How should firms strategically allocate managerial attention among workers? We formulate a theory that illustrates how different attention allocation strategies influence workers' updated beliefs about the manager's type, and, in turn, employee performance. To test the theoretical predictions of the model, we conduct a 6-month randomized control trial at a leading multi-national spa chain with 157 stores and more than 10,000 workers in China. In the experiment, managers are given a weekly list of employees with whom they are required to have a standardized, private conversation. We compare the random allocation method, where attention allocation is uncorrelated with any employee characteristics, to the directed allocation method, where managers focus on employees with more negative emotions and therefore higher attrition probabilities. We document significant causal effects of managerial attention on employee attrition and well-being. Consistent with the theory, we find that random allocation of managerial attention is more effective than directed allocation in reducing turnover.

JEL Codes: D23, J22, J24, L23, M50

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1 Introduction

The impact of human resource management on employee and firm productivity has received widespread attention in the economics and management literature (Huselid, 1995; Koch and McGrath, 1996; Ichniowski et al., 1997; Lazear, 1999; Bloom et al., 2013). An important strategic resource that firms rely on to improve employee performance is managers (Coff, 1997; Adner and Helfat, 2003; Belenzon and Schankerman, 2015). Middle managers are especially pivotal in the workplace, because they directly interact with employees, implement management practices, and administrate the work process. While previous scholarship has broadly examined the link between middle manager characteristics and employee performance (Bandiera et al., 2007; Augier and Teece, 2009; Castilla, 2011; Lazear et al., 2015; Bonet and Salvador, 2017; Briscoe and Joshi, 2017; Pierce et al., 2020b; Friebel et al., 2021; Hoffman and Tadelis, 2021), less attention has been devoted to how managerial resources should be allocated among workers. This study is designed to bridge this gap.

We focus on an important aspect of managerial practice–managerial attention allocation–and address two research questions. First, what is the causal impact of managerial attention on employee attrition, productivity, and well-being, as well as firm performance? Second, how should a firm strategically allocate limited managerial attention amongst its workers? In particular, should managers focus on frustrated or low-performing workers, or should they check in with employees non-discriminatorily? In this paper, managerial attention refers to managers' regular interaction with employees to make them feel cared for and respected.

To study the impact of managerial attention allocation on employee attrition, productivity, well-being, and firm performance, as well as its underlying mechanism, we conducted a 6-month randomized control trial (RCT) at a leading multi-national spa chain with over 10,000 workers in its Chinese division, assigning 157 stores to two equal-sized treatment cells and a control cell. Managers from the two treatment groups were given a weekly list of employees with whom they were required to have a private conversation. We used different methods to generate the employee lists. In the directed attention allocation group (T1), managerial attention was directed towards employees who expressed negative emotions and thereby higher attrition probabilities as reflected in the high-frequency employee survey results. In the random attention allocation group (T2), employees were chosen randomly and thus attention allocation is uncorrelated with any employee characteristics or performance statistics. Workers have similar work environments across all stores, carry out the same tasks, and are paid according to the same compensation scheme. Managers from both groups talk to the same proportion of store workers each week. Hence, the only difference between the two treatment groups is how managers allocated their attention. This allows us to isolate the impact

of the managerial attention allocation strategy, which is often correlated with manager characteristics or people skills. We collected a pre-intervention baseline round of surveys, continuous midline surveys, and a post-RCT round at the end of the experiment. These consolidated datasets allow us to distinguish among several competing mechanisms.

The firm setting is well-suited to study the impact of managerial attention allocation. First, the firm is a typical service sector chain that employs large numbers of low-skilled workers. Workers are divided into teams of 10 to 20 and middle managers have frequent face-to-face interactions with their team members. The setting is thus representative of many service sector firms worldwide. Second, the richness in both individual-level and store-level administrative, turnover, productivity, and survey data allows us to conduct a comprehensive evaluation of managerial attention and to disentangle the mechanisms behind it. Third, the high-frequency survey data enables us to capture workers' daily emotions. The information makes it possible for managerial attention to be allocated strategically.

The six-month experiment yielded several interesting results. First, the attrition rate of the random attention group dropped by 13.9% in contrast to a statistically insignificant 7.9% drop in the directed attention group. Second, random allocation of managerial attention raised store-level revenues by 6.6%, whereas directed attention allocation yielded no results. In particular, managerial attention was more effective for smaller stores and those with higher baseline turnover. Third, managerial attention significantly improved employee job satisfaction, evaluation of managers, stress, and mental health. Interestingly, compared to the other two groups, evaluations of managers increased more significantly in the random allocation group. Using a combination of theoretical, experimental, empirical, and qualitative approaches, we show that random allocation is more effective because workers make inferences about a manager's motive and type based on the attention allocation strategy. Managerial attention can be motivated by a genuine care for subordinates or a more selfish focus on raising one's own payoff given that it is tied to team performance. A manager who is attentive to her team in general could potentially be either caring or selfish. One who only interacts with unhappy or less productive workers, however, reinforces workers' belief that their manager is more likely to be the selfish type, which undermines the effect of managerial attention.

There are some obvious alternative explanations for the results. First, can the results be driven by differences in the managers' implementation of the experiment? To address this concern, we compare the two treatment groups in terms of both the number and quality of conversations and find no differences between them. Second, can the results be due to the random attention group's worker feeling monitored by their managers because of the less predictive conversation timing? To examine this, we compare the individual labor supply and productivity of the two treatment groups and find no discernible differences. Third, perhaps directed attention was targeting the wrong group of workers? For instance, demoralized

workers may have already made up their minds to leave, which would greatly limit the marginal value of spending time on these workers. To examine this, we assemble our implementation, survey, and attrition data to find that timely conversations with workers who experienced upsetting incidents significantly reduced turnover rates. Finally, could the results be driven by the Hawthorne effects, where managers behave differently because they are being studied? This is unlikely as well because the Hawthorne effects cannot explain differences between treatment groups, as any Hawthorne effects should cancel out.

This paper links the theoretical and empirical literature on the value of middle managers (Lazear et al., 2015). Prior scholarship tries to open the black box of how managers can influence individual and team performance. Earlier studies have explored managerial effort and task allocation (Bandiera et al., 2009; Amodio and Martinez-Carrasco, 2018; Adhvaryu et al., 2019), feedback (Ashford and Tsui, 1991; Brett and Atwater, 2001; Seifert et al., 2003), time use (Bandiera et al., 2020; Giurge et al., 2020), and cognitive skills (Helfat and Martin, 2015; Helfat and Peteraf, 2015; Maitland and Sammartino, 2015; Sharma and Tarp, 2018). Our work expands the discussion on the roles of manager's people management skills and face-to-face interactions with employees. For example, within the high-tech industry, Hoffman and Tadelis (2021) show that survey-measured people management skills have a strong negative relation to employee attrition. In another study, Friebel et al. (2021) demonstrate that middle managers reduce personnel turnover by spending more time interacting with employees through a field experiment at a large European retail chain. The key contribution of this study is that it sheds light on how a manager could allocate her time and attention among different employees to reduce turnover more effectively. While there have been a number of empirical tests of the effect of people skills or attention, we propose a novel theory and a field experiment to explore the manager-employee interaction problem through the perspective of resource allocation.

Second, the paper is related to the literature on incomplete contracting within firms. In particular, our results can be interpreted through the lens of relational contracts. Building on the insight of the "shadow of the future" (Kreps et al., 1982) where repeated games present greater opportunities for cooperation, a relational contract is a non-legally binding understanding between two parties that typically describes how one party should behave and how the other will reward the expected behavior (Baker et al., 1994, 2002; Levin, 2003; Chassang, 2010; Gibbons and Roberts, 2013; Helper and Henderson, 2014; Argyres et al., 2020; Barron et al., 2020). As a result, holding contractual management practices constant, less tangible firm attributes such as relational contracts or trust can, in turn, drive differences in productivity (Ichniowski et al., 1997; Gibbons and Henderson, 2012). Despite compelling theoretical results and the ubiquity of informal contracts, as documented in case studies, systematic empirical evidence exploring these ideas has been limited (Gil and Zanarone, 2018). Similar to Blader et al. (2020), our experiment can be understood as a conscious effort on the part of the firm to change the relational contract between its workers and managers,

with a focus on employee beliefs about the nature of their relationship with their manager. A different strand of literature, closely related to the idea of designing implicit contracts to align employee incentives with firm objectives, underlines the importance of reciprocity and a culture of trust in the presence of incomplete contracts (Akerlof, 1982; Dur, 2009; Kube et al., 2012; Elfenbein and Zenger, 2014, 2017; Meier et al., 2019). Empirical evidence on gift exchange has been mixed (Gneezy and List, 2006; Falk, 2007; Maréchal and Thöni, 2019). Interpreting attention from managers as a form of gift, we contribute to this discussion by providing moderate support for positive reciprocity on non-pecuniary gift exchange.

In addition, this paper also speaks to the literature on the attention-based view of the firm (Ocasio, 1997). Research in organization theory, strategy, and economics have highlighted the role of organizational attention in strategic decision making and adaptation (see for instance Ocasio, 2011; Eggers and Kaplan, 2013; Helfat and Peteraf, 2015; Vuori and Huy, 2016; Ocasio et al., 2018 in management and Bertrand and Schoar, 2003; Dessein and Prat, 2016; Halac and Prat, 2016; Dessein, 2020 in economics). Much of the literature focuses on how firms and managers should selectively allocate their attention across a set of tasks or problems. For example, Lo et al. (2020) find that managers tend to allocate more attention to tasks in which they possess more expertise when attention is scarce. Instead, we focus on how managers should allocate attention within the same task across different types of employees. In our study, two groups of managers carry out the same task of communicating with employees, allocating the same amount of time and effort. We complement existing studies by being the first to document robust evidence on the strategic allocation of managerial attention across employees.

Lastly, this paper contributes to the burgeoning literature on the impact of management practices on employee turnover and productivity (Ichniowski et al., 1997; Lazear, 1999; Chan et al., 2014; Bloom et al., 2015; Gubler et al., 2016; Friebel et al., 2017). In particular, it relates to a set of experiments on the adoption of managerial practices or process innovation like Bloom et al. (2013), Blader et al. (2020), Gosnell et al. (2020) , Pierce et al. (2020a), and Sandvik et al. (2020). The value of human resource management practices are well-recognized by management scholars (Huselid, 1995; Koch and McGrath, 1996; Ichniowski and Shaw, 2003). More recently, a growing trend in the field places emphasis on the adoption of "innovative" human resource management practices enabled by the advance in monitoring technologies and increasing use of data-driven management. However, some evidence shows that this quantification of work can reduce productivity in cases where the work is complex (Ranganathan and Benson, 2020). By causally identifying the impact of a non-performance-based human resource practice, this paper provides theoretical and empirical support for the importance of pro-social motivation in determining employee behaviors in a real-world labor setting.

2 Model

In this section, we present a simple model to illustrate how the allocation of managerial attention influences employee attrition, job satisfaction, and performance. The purpose of the stylized model is to highlight how the allocation method of attention impacts employee beliefs and view of the manager, and hence their decision of whether to stay.

Suppose managers are one of two types, altruistic or selfish, denoted by $m \in \{A, S\}$, and employees hold prior belief that $P(m = A) = p^0$. Each manager has limited attention, π, to be allocated among her subordinates.

A measure 1 of workers work for each manager. Each worker can be one of two types $i \in \{L, H\}$, with L indicating low performance and a high potential for improvement, and H high performance and a low potential for improvement. Suppose $\bar{X_L}$ proportion of workers are of L type, with $\bar{X_L} > \pi$. In other words, managerial attention is scarce even among workers of low performance.

Conditional on getting attention from the manager, the worker i's expected payoff from continuing to work in the firm is given by,

$$U_i = U_0 + \mu_i(a_i + \beta p_A) - \frac{1}{2}a_i^2, \qquad i \in \{L, H\}$$

where μ_i is the potential for improvement which, by definition, $0 < \mu_H < \mu_L < 1$; a_i denotes the additional effort of worker i; p_A is worker belief that the manager is of the altruistic type; and β captures the worker sensitivity to manager type. Thus, the optimal choice of effort for worker i, given belief p_A, is $a_i = \mu_i$. If the worker decides to quit his job, then he can pursue an outside option that yields $\underline{U}$. A worker will stay in the firm, denoted as $q_i = 0$, as long as $U_i \geq \underline{U}$; otherwise, the employee will quit, $q_i = 1$. Let Q denote the proportion of workers who quit.

There are two strategies for allocating attention, random or directed, denoted by $t \in \{R, D\}$. To simplify the analysis, henceforth assume the workers who are not given attention will be unaffected by this communication. Ignoring spillover effects, we focus on those workers who receive attention from their managers. A manager m's payoff depends on both her subordinates' improved efforts conditional on staying with the firm and how she allocates her attention. Specifically, let α denote the weight a manager places on the performance of her workers. If the manager is of the selfish type, her payoff is given by

$$U_S = \alpha \int a\mathbf{1}_{\mathbf{q_i=0}} - c\mathbf{1}_{t=R}.$$

Whereas if the manager is of the altruistic type, her payoff is given by

$$U_A = \alpha \int a\mathbf{1}_{\mathbf{q_i}=\mathbf{0}}.$$

In other words, random allocation of attention takes a toll on managers of the selfish type. This assumption is based on the observation that a goal-oriented and pragmatic manager would find it unnatural to chat with subordinates at random as opposed to directing her attention to a selected subset of workers based on revealed worker information with an aim to maximize performance improvement.

The timeline of the game is as follows:

1. Periodic surveys elicit worker i's truthfully reported type and data is relayed to their manager.
2. Managers choose how to allocate their attention.[1] Some workers receive attention.
3. Workers choose whether to quit. Payoffs are realized.

To foreshadow the prediction of the model, first note that holding all else constant, a worker's expected payoff increases with his belief that his manager is the altruistic type. Given a fixed outside option, the higher a worker's expected payoff for staying with the firm, the less likely he is to quit. This captures the fact that a worker's payoff from a job includes a non-pecuniary component in addition to his wages. An altruistic manager who builds a more trusting relationship with her subordinates in turn enhances their working experience. Secondly, holding fixed workers' posterior belief about their manager's type, the resulting improvement in performance, i.e. the impact of attention, is indeed higher for L-type workers than for H-type workers. This presents the manager with a trade-off between attention allocation strategies. Given that selfish-type managers find it costly to randomize attention, this type is likely to choose to direct their attention solely towards low-performance workers. As assumed, this action alone will exhaust their capacity to give attention, since $\bar{X_L} > \pi$. Given this, altruistic-type managers may choose to randomly allocate their attention in order to set themselves apart from the selfish type. The resulting separating equilibrium would hence reveal manager type perfectly. In this separating equilibrium, an H-type worker can attain higher expected payoff than an L-type worker upon receiving attention. This is because, once bestowed attention, the H-type worker infers with certainty that his manager must be the altruistic type. The L-type, however, is still uncertain of his manager's type and updates his belief according to Bayes' rule. So if the updated belief of the L-type is still low,[2] and at the same time, workers care greatly about manager

[1] In the experiment, managers are given the allocation method. However, neither the manager nor the employees are informed of this crucial aspect of the experiment design.

[2] This can be due to either a low prior of his manager being the altruistic type (small p^0) or there being only a small portion of L-type workers (small $\bar{X_L}$).

type (β is large), then a manager giving attention to an H-type worker could yield higher expected payoffs than to an L-type worker, thanks to the "premium" of demonstrating oneself as the altruistic type.

Indeed, such a separating equilibrium exists if $c > \alpha\pi\mu_L$ and $\frac{1}{2}\mu_H^2 + \beta\mu_H > \frac{1}{2}\mu_L^2 + \beta\mu_L p'_L$, in which $p'_L = \frac{p^0 \bar{X_L}}{p^0 \bar{X_L} + 1 - p^0}$.[3] Under these conditions, managers self-sort into attention allocation methods, with the selfish type resorting to directed attention towards only a subset of the L-type while the altruistic type randomly allocates their attention up to capacity. Moreover, because H-type workers attain a higher expected payoff than L-type workers, random allocation beats directed attention on average in terms of lower attrition rates.

Now,we can formally state the following main hypothesis.

Hypothesis 1a. If the measurable performance change induced by attention is not sufficiently large while workers care about manager type, then the random allocation method lowers attrition rates more than the directed attention method, which still lowers attrition rates compared to no attention at all.
It is straightforward that any allocation of attention is better than no attention, as attention has the direct benefit of enhancing employee payoff. The key, however, is that there is a trade-off for directing attention to those who are at the margin of quitting. This is because employees infer manager type and thereby also infer their expected future payoff from the allocation method of the current period. Random allocation indicates that the manager cares about the general welfare of her team, rather than just their productivity. This in turn translates into a higher expected future payoff for employees, making the option of staying with the firm more attractive.

Because turnover is costly for the firm, a corollary of this hypothesis is as follows:

Hypothesis 1b. The random allocation method increases revenue due to lower attrition rates.

Other implications of the model — such as random allocation of attention leading to a higher evaluation score of the manager by the workers,[4] and stores previously suffering from a higher attrition rate seeing better outcomes after attention allocation[5] — will also be taken to the data for testing.

[3] For example, the set of parameter values such as $p^0 = 0.3$,$\bar{X_L} = 0.2$,$\pi = 0.1$, $c = 0.05$, $\alpha = 0.1$,$\mu_H = 0.2$, $\mu_L = 0.4$, and $\beta = 2$, satisfy both the conditions and thus support a separating equilibrium wherein selfish-type managers direct their attention while altruistic-type managers randomize their attention among workers.

[4] As long as the evaluation score of the manager is positively correlated with worker beliefs on the manager being the altruistic type, this result holds. Indeed, as explained in more detail in Section 5, the survey results show that a higher proportion of workers from the random allocation group (55% vs. 47%) perceive managers to be "altruistic". In addition, the survey also finds that a manager's motive influences worker's opinion of them. When a worker knows the manager talks to him because she cares only about team performance, his evaluation of the manager drops.

[5] Attention allocation has the direct benefit of enhancing the worker's expected payoff of working in the firm. Stores previously suffering from a higher attrition rate have more workers on the verge of quitting and thus achieve higher attrition reduction

3 Research Design

3.1 The Firm

Our firm of study is a leading multi-national spa chain headquartered in China. Founded more than 20 years ago, the firm operates more than 500 stores worldwide in hundreds of cities. As an early pioneer in franchised massage services, the firm is the largest of its kind in China. The company offers a wide range of spa and therapeutic massage services[6] and serves more than five million customers annually. Figure 1 displays photos of the company's spa stores and employees.

Our study focuses on 157 stores dispersed geographically across China. At the time of the experiment, each store employed 43 workers on average. The company has five layers of personnel: senior executives, regional managers, store managers, middle managers, and workers. While the workforce is relatively stable within the upper three tiers, the bottom tier experiences high turnover, with an annual turnover rate well above 100 percent. Each store consists of a store manager, multiple middle managers, and roughly three types of workers, with two-thirds of the workers being spa workers. Figure 2 demonstrates the organizational structure within a store.

Spa workers' job responsibilities include providing massage services, maintaining client relationships, and selling the pre-paid store gift cards or personalized service packages.[7] While workers sometimes help each other out, individual worker productivity is largely independent of the effort of other workers. Employees typically work six shifts a week, scheduled in advance by the store managers. The spa worker compensation scheme is comprised of a piece-rate plus task bonuses and sales commissions. On average, an experienced spa worker's monthly compensation is around ¥10,000 ($1,600), which is quite high among service sector employees. Task bonuses and sales commissions are linear functions of the number of returning customers and sales volume, with small adjustments for attendance.

Store managers run the everyday business of stores. They supervise the store's operations and fulfill several human resource management duties, including offering employee training sessions, overseeing attendance and performance, maintaining employee and customer relationships, and distributing workers' pay cheques. Middle managers, who typically lead a team of 10 to 20 workers, are rewarded for both their own sales as well as the performance of the team they lead. In particular, middle managers are strongly incentivized to improve the performance of their team for great personal compensations and promotion

due to the intervention.

[6] Therapeutic massage incorporates a variety of advanced modalities that enhance the body's natural restorative functioning. Examples of services include hot stone massage, back oil massage, complete massage, and deep tissue massage.

[7] The personalized service package is tailored to each customer's needs. For instance, a customer suffering from back pain would prefer a specialized back massage to a standard service.

opportunities. Finally, all stores provide the same services and operate under common compensation schemes and management policies.

3.2 Turnover Problem and Rationale for RCT

The spa chain's employee turnover, especially among lower level workers, is quite high. For this firm, because involuntary attrition (firing) is extremely rare as low-performing employees tend to quit voluntarily, turnover is mainly due to voluntary attrition. During our period of study, average monthly turnover rate was 13% and average job tenure was 1.22 years. Turnover rates are particularly high among new hires: more than half of the workers quit within three months of starting. Workers who stay beyond one year, however, become a relatively stable part of the chain's workforce.

We interviewed over one hundred workers to understand the underlying reasons for turnover. The most common problem, especially for new workers, is that many are not used to the working style of the spa industry. For instance, most tasks are scheduled in the afternoon and late evenings, and the work days are typically long. Administering massage therapy is also both physically and mentally exhausting. Each task takes over an hour and a half and workers feel drained after completing four or five such tasks within the same workday. Some workers report health issues after the intensive work and request a leave of absence from work. Secondly, as is the case for most low-skilled industry jobs, new workers may not be satisfied with the compensation and decide to look for better paying opportunities elsewhere. Third, employees tend to leave when they dislike their managers or certain management practices. During our interviews, workers reported many concrete examples of good and bad managerial practices. Many are particularly motivated when their bosses go an extra mile to treat them well such as giving them a ride home after a long workday. Conversely, some report frustration when their bosses handles their responsibility poorly such as favoring a selected group of workers over others. This is consistent with the literature on the value of bosses and human resource practices (Ichniowski et al., 1997; Lazear et al., 2015), and points to possible directions for improvement to reduce employee turnover.

Senior management has also expressed concern over the excessively high turnover rates. While some employee turnover is healthy and efficient in adjusting labor input (Siebert and Zubanov, 2009), high levels of turnover are highly costly for the firm (Friebel et al., 2021), through higher short-staffing costs and on-boarding costs, more incumbent workers' recruitment activities, and reductions in team morale after a departure is announced (Kuhn and Yu, 2021).[8] All these activities raise the administrative cost at the firm level.

[8] According to Kuhn and Yu (2021)'s calculation, the turnover of a single employee reduces profits by an amount that represents 9.4 days of per-employee net sales, or 1.1% of a worker's net sales over a 2.3-year career.

Store managers are likewise frustrated with how the high turnover rate influences their day-to-day operations. Our conversations with fifteen store managers not only confirm the significant wasted time investment for training each worker and negative impact on employee morale, but also reveal that "*customers lack a sense of security because their service workers keep changing... When our workers are unstable, so are our customers. There are several cases where customers stop visiting our store because their service workers left.*" Comments from local managers confirm that the high turnover interrupts their business and takes a toll on the firm's operations and business revenues.

In July 2018, we conducted extensive field visits to multiple stores of the firm to address the issue. A main concern of the Chairman and C-suite executives is that turnover has been so high that they are having great difficulty filling some of the job vacancies. To understand the impact of managerial attention on firm performance and to better allocate limited managerial attention, the firm agreed to collaborate with us on a 26-week experiment. Based on both theoretical predictions and qualitative evidence from our field interviews, we proposed that the managers initiate regular conversations with workers in general (as opposed to strategically targeting underperforming workers specifically) in order to significantly reduce employee turnover.

3.3 The Experiment

We conducted a 6-month RCT at 157 stores of the spa chain with over 10,000 workers from April 1, 2019, to September 30, 2019. The design was registered at the beginning of the experiment.[9] The 157 stores were assigned into one of three groups: directed attention group (T1), random attention group (T2), and the control group. Middle managers in the treated stores were given a list of employees with whom they were required to have a one-on-one conversation over the following week. The conversation follows a standardized format, with an aim to provide care and support to workers. About one-quarter of the total number of active store workers[10] were drawn each time, with each manager, on average, talking to 2 to 6 employees per week.[11] Each conversation takes 15-to-20 minutes. Managers are asked to choose from a range of topics within the provided talk-to-me toolbox. After each conversation, managers complete an interview log and submit it online to headquarters for review. Figure A1 shows the interview log and the conversation format. Figures A2 and A3 display the toolbox. In the control group stores, none of the management practices were changed throughout the experiment period.

The employee lists are generated differently for each of the two treatment groups. In the direct at-

[9] The RCT registry number is AEARCTR-0004280. The experiment has been waived by Stanford IRB for approval.

[10] This includes spa workers, assistant spa workers, and professional sales associates.

[11] During our training sessions, we emphasize the purpose of the conversations to treatment group middle managers as one of providing care and support. In particular, we highlight that the purpose is NOT monitoring worker performance.

tention group (T1), employees are chosen according to their employee survey results from the previous week. This mandatory high-frequency survey, conducted through the firm's employee app system,[12] is designed to capture employee emotions and mental health. We select employees with the lowest survey scores from the past week. In the random attention group (T2), employees are chosen randomly through a random number generator. Thus, managerial attention is not correlated with any employee characteristics, attrition likelihood, or performance measures. To prevent the potential pitfalls of too many conversations with any one employee, such as perceived favoritism, we set a cap of two conversations per worker per month for both treatment groups.

Experiment Implementation. On March 17, 2019, the headquarters' operations department sent a notification to middle managers in the treated stores to receive a one-hour training. From March 17 to March 23, the operation department held multiple training sessions for middle managers in the treated group. The managers also received the interview log and a talk-to-me toolbox containing a detailed list of different topics of discussion. During the week of March 25 to March 31, the operations department held an orientation week for middle managers in the treated group to familiarize them with the procedures and to report any implementation problems. The experiment began on April 1 and concluded on September 30, 2019. Figure 3 shows a detailed timeline of the RCT. Only the senior management team, regional managers, and a few staff from the operations, HR, and information technology (IT) departments knew about the actual experiment. Neither workers nor managers were informed that an RCT was occurring. Managers from the treated stores only knew that they were tasked with carrying out quality conversations with the specified list of workers, and the announcement was framed as a policy change. Managers did not know how the lists were generated, and managers of the two treatment groups did not know about the different methods used to generate their respective lists.[13] In this regard, we ensure that neither managers nor workers perceived themselves as experimental subjects or gamed the policy during the implementation process.

At the end of each week, the research team and operations department sent the detailed lists of employee names to middle managers in the treated group. Managers then confirmed whether any workers were on vacation, sick leave, or needed to be replaced for other legitimate reasons. After each list was finalized, managers carried out one-on-one conversations with all the listed workers and submitted the interview log after each conversation. The interview logs were graded by a graduate research assistant (RA)

[12] Similar to Amazon's daily employee survey system, the spa chain's survey asks workers to answer one survey question within 1 to 3 days. Several different dimensions are covered, including but not limited to job satisfaction, evaluation of bosses, stress levels, and mental health conditions. All company employees must complete the questionnaire before they can log onto their staff account.

[13] Managers were told the list was generated according to reasonable methods and believed the list was fair. Managers understood their major task is to hold high-quality conversations with employees.

for quality control[14] according to four different scales: excellent (1.25), OK (1), poor (0.8), implementation failure (0). To ensure that managers were not simply filling in logs without having quality conversations, RAs also looked into timely feedback from the regional managers, store managers, and employees as a quality check.[15] According to the feedback from store managers and employees, the interview log score is a pretty accurate measure of implementation quality. Since interview log scores are not tied to a manager's personal compensation, low-performing managers generally do not bother writing good logs. In total, we collected and graded 22,822 completed interview logs with a compliance rate of above 99%.

Randomization. Pre-treatment data for the spa stores span from July 2017 to March 2019. We use these 21 months of pre-treatment data in our stratified randomization methods, stratifying on turnover rate (our major dependent variable), store revenue, and store size. The 157 stores were randomized into three RCT arms. Table 1 shows that the three groups are well-balanced over the observables. In each row of columns 1-4, we regress each pre-RCT observable on the two treatment dummies. Column 1 reports the control group means. Columns 2 and 3 report the differences between each treatment group and the control group. Column 4 shows the p-values for the F-statistic of the joint significance of the two treatment indicators for each variable. None of the treatment dummies are statistically significant. Columns 5 and 6 compare the treated stores (random and directed attention groups) to the control stores and only the mean age of the store is marginally significant. None of the other dummies are statistically significant.

RCT Validity. There are two immediate concerns for an RCT like ours. First, it is crucial that our survey questions incentivize workers' truthful reporting of their emotions and mentalities. This is not a concern in our setting for several reasons. First, the firm's IT and HR departments conducted multiple tests before launching the daily employee survey system. Since an employee only receives one survey question every one to three days, the effort required to complete this task is extremely low and the proportion of valid answers is above 90% for each survey question.[16] Moreover, since we calculate worker's weekly average survey scores, any noise is likely to cancel out. Furthermore, we conducted multiple testing before the experiment to check if workers were afraid of expressing themselves and find no such evidence. In survey questions collecting workers' thoughts and critiques for 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. Indeed, since corporations are gradually turning into large gig platforms for workers, where

[14] Six graduate RAs were in charge of overseeing the experiment implementation and grading. We provided detailed training and grading rubrics for all the RAs.

[15] For instance, the employee is asked in survey questions of whether her manager talked to her during last week and how the experience was.

[16] The IT department develops sophisticated algorithms based on historical survey data to calculate the accurate response rate, i.e., whether one chooses "I am unhappy" because she is unhappy, or because she clicks on one answer randomly.

workers enjoy great flexibility and can always quit if they are unhappy, we are not worried that workers dare not speak their mind. Finally, as shown in Section 5.2, we provide evidence that workers' survey outcomes are strongly correlated with their own attrition probability. This further confirms that the continuous surveys successfully capture worker emotions and mental states.

Second, workers must not know that managers are deciding on who to talk to based on an assigned list. A crucial part of our theory is that workers make inferences about the manager's type based on the way she allocates her time and attention. A rational worker who knows the manager is talking to him because she is required to do so by her superiors should not update his belief. This is not a concern either, as none of the workers know about the RCT or the assigned lists. Furthermore, as suggested by our second round of survey experiment, few respondents suspected that the manager was required to talk to them.

Data and Measurement. We assemble the firm's personnel and accounting data from July 2017 to September 2019 to create worker-month and store-month panels. Our analysis mainly uses five sources of data. First, we draw on the monthly attrition data at both the individual and store levels. Second, we collect the monthly productivity data on individual employees and stores.[17] Individual-level productivity variables include days of attendance, the share of returning customers,[18] sales,[19] and compensation.[20] Store-level performance is measured by monthly store revenues and number of customer visits. Third, we collect individual employee demographic information (including gender, entry age, schooling, race, and marital status) and the store's administrative information (e.g. employee number, store size, history, revenue, turnover, and location). Fourth, we obtain the implementation data of every conversation including the timing of every conversation, the quality score of each conversation, and the number of conversations.

Finally, we use survey data collected before and after the experiment to assess the average treatment effect on employee well-being. The survey data covers four different dimensions including job satisfaction, evaluation of managers, stress levels, and mental health. We also exploit part of our experimental period of survey data to analyze the impact of manager-worker conversations on worker attrition. Job satisfaction topics include overall job satisfaction, trust, sense of belonging, willingness to recommend the company to friends or family, and willingness to stay. Manager evaluation questions include managerial care, problem-solving, whether an employee is willing to turn to their managers for help, how easy it is to ask for a leave,

[17] Attrition is coded as 1 if an employee leaves during that month and 0 otherwise.

[18] One key measure of worker productivity in the spa industry is "customer picks". Suppose that, when a customer visits a store for the first time, the store randomly assigns a worker to the customer. Depending on the customer's satisfaction with the service rendered, she may request a specific service worker during her next visit. Workers who get picked by customers receive an extra bonus. The share of returning customers is calculated by the number of customer picks divided by the total number of tasks. This variable measures each worker's ability to retain customers.

[19] Each worker's individual sales is calculated by the sum of pre-paid gift card sales and personalized service package sales.

[20] The compensation scheme is piece-rate plus task bonuses and sales commissions. Monthly compensation, therefore, is the weighted sum of one's full productivity.

and fairness. For mental health questions, we use the Warwick-Edinburgh Mental Wellbeing Scales[21] and cover ten different dimensions of mental health measures such as optimism, exhaustion, and curiosity. Figure A4 shows a representative list of sample survey questions used in this study. In addition to these data, we conducted over a hundred interviews with workers and managers in 2018 and 2019 to understand the mechanisms.

3.4 Econometric Analysis

We estimate the average treatment effects of managerial attention allocation strategies using two simple econometric frameworks. We report both the treatment versus control estimator and the difference-in-difference (DID) estimator in our analysis. We use the following estimating equation for the treatment versus control estimator:

$$Y_{ijt} = \beta_1 \times T_{1i} + \beta_2 \times T_{2i} + \tau_t + \gamma_j + \epsilon_{ijt} \tag{1}$$

where Y_{ijt} is the post-treatment outcome (e.g., attrition, productivity, job satisfaction) of individual i from store j in month t, T_{1i} and T_{2i} are the two treatment dummy vectors, τ_t is month fixed effects, γ_j is store fixed effects, and ϵ_{ijt} is the idiosyncratic error term clustered at the store level.

The difference-in-difference estimation uses the following regression equation:

$$Y_{ijt} = \beta_1 \times T_{1i} + \beta_2 \times T_{2i} + \beta_3 \times post_t + \beta_4 \times T_{1i} \times post_t + \beta_5 \times T_{2i} \times post_t + \tau_t + \gamma_i + \epsilon_{ijt} \tag{2}$$

where $post_t$ is a dummy variable equal to 1 for all months from April 2019 to September 2019 and 0 for all months from January 2018 to March 2019, and γ_t is store fixed effects. In contrast to the treatment versus control estimator, we use both pre-treatment and post-treatment data to estimate the DID equation.

To estimate the heterogeneous treatment effects, we interact several above-median indicators of pre-specified variables with treatment dummies:

$$Y_{iit} = \beta_1 \times T_{1i} + \beta_2 \times T_{2i} + \beta_3 \times R_i + \beta_4 \times T_{1i} \times R_i + \beta_5 \times T_{2i} \times R_i + \tau_t + \gamma_i + \epsilon_{it} \tag{3}$$

where R_i is an indicator for an above-median baseline value of each pre-specified variable. The notation for equation 3 is otherwise analogous to that of equation 1. In this equation, $\beta_1 + \beta_4$ and $\beta_2 + \beta_5$ are the estimated treatment effects of the two treatment dummies on individuals with an above-median baseline

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

value of the specified variable; β_1 and β_2 are the estimated treatment effects on workers with a below-median baseline value; and β_4 and β_5 are the estimated differences between the two treatment effects. In the heterogeneous analysis section, we report β_1, β_2, $\beta_1 + \beta_4$, $\beta_2 + \beta_5$ and the p-values for β_4 and β_5.

4 Results

In this section, we move to the main analysis where we study the impact of managerial attention allocation on employee performance. We begin by assessing the effects of directed and random managerial attention on individual performance. In particular, we explore how managerial attention allocation influences employee attrition and productivity. Second, we examine the effect of managerial attention on store-level performance. Third, we look at the causal effect of managerial attention on individual-level survey outcomes, including job satisfaction, evaluation of managers, stress level, and mental health conditions. Finally, we discuss whether the treatment effects are heterogeneous across stores, such as those that differ by worker age composition, size, and baseline turnover rate.

4.1 Average Treatment Effects on Individual Performance

Figure 4 shows the average number and quality scores of conversations for each week in the two treatment groups during the experiment. Overall, treated store managers completed 22,822 standardized one-on-one conversations with workers in 26 weeks, with completion rates over 99%.[22] On average, managers held about 8.4 weekly conversations in each store and the mean conversation quality score is above 1.1 on a 0-1.25 scale. Figure 4 reveals two patterns. First, the average number of weekly conversations across the two treatment groups is very comparable. Second, the quality of conversations is similar. Therefore, differences in performance between the two treatment groups are unlikely to be driven by any differences in experiment implementation. Indeed, all the treated store managers received the same training to communicate with workers in professional manners using a standardized format. None of the managers knew that the employee lists were generated using different methods and we expect the implementation processes to be identical.

Table 2 presents the causal impact of managerial attention on employee attrition. The dependent variable is whether a worker quits within a month. Regression coefficients are multiplied by 100 for ease of readability. All regressions are at the worker-month level and standard errors are clustered at the store level. Columns 1 and 2 report the treatment versus control estimators and use the experimental period of data between April and September 2019. Columns 3 and 4 report the DID coefficients using the data

[22] Completion rate is calculated by the number of finished conversations over the number of assigned conversation tasks.

from January 2018 to September 2019. Column 1 shows that the random allocation of managerial attention reduces the monthly attrition rate by 1.61 percentage points, corresponding to a reduction in attrition rate by 12.3%. The coefficient is statistically significant at the 5% level. Relative to workers in the control group stores, workers in the directed attention group have monthly attrition that is lowered by 0.81 percentage points, equivalent to a reduction in attrition by 6.2%. The magnitude of the coefficient is smaller and not statistically significant. Column 2 compares treatment versus control groups and shows that managerial attention reduces the monthly attrition rate by 1.26 percentage points (or 9.6%) on average. Columns 3 and 4 repeat the analysis using a DID framework. We find that the treatment effects are 13.9% and 11% for the random attention group and the entire treatment group, respectively. Both regression coefficients are statistically significant. Similarly, we do not find directed managerial attention to be effective in reducing the attrition rate: the coefficient is smaller and not statistically significant. Together, the results suggest that managerial attention has a substantial effect on employee attrition. Interestingly, compared to the directed attention allocation method, random managerial attention allocation is more effective in reducing worker attrition.

Table 3 explores the impact of the different managerial attention allocation strategies on individual labor supply and productivity. We use both pre-RCT and RCT data in all four columns. Columns 1-4 analyze the impact of managerial attention on individual workers' monthly attendance, the share of repeat customers, sales, and compensation respectively. We fail to find any effects of managerial attention on individual-level labor supply or productivity: none of the coefficients have any statistical significance and all of them are small in magnitude. Since conversation is designed to provide employees with attention and care, rather than to coach sales techniques, we expect the impact on productivity to be minimal. The result also provides suggestive evidence that the impact on attrition is unlikely to be driven by the stress of being monitored. One potential mechanism is that, under the random attention allocation scheme, managers might talk to a worker at any time. A worker could be worried that the manager might check in unexpectedly, such as through conversations, in an attempt to deter shirking. This is unlikely to be the case because no evidence suggests that workers who randomly receive managerial attention are changing their labor supply or being more productive.

Together, we show that the effect of managerial attention on employee attrition is substantial, especially when it is randomly allocated. The difference is unlikely to be caused by workers' feeling of being monitored when their managers talk to them at random. Neither attention allocation strategies have a significant impact on individual labor supply or productivity.

4.2 Average Treatment Effects on Store Performance

A stated goal of managerial attention, especially random attention, is to improve firm performance through lower costs of attrition. We thus hypothesize that the random attention allocation strategy raises store-level revenues compared to the other two groups since turnover rates drop in stores using random attention allocation.

Table 4 reports the effect of managerial attention on store-level performance. The dependent variables are the log of store revenues and the log of store customers. We further control for store-level characteristics, month fixed effects, and region fixed effects. Column 1 shows that managerial attention raises store-level revenues by 6.6% in the random group. The coefficient is statistically significant at the 5% level. In contrast, the directed allocation strategy has no effect on store revenue. Column 2 estimates the effect of managerial attention on the number of customer visits and shows that neither allocation method has any impact. This indicates that the random attention group's higher revenues are not caused by a larger number of customers from the supply side of the market.

Interestingly, while the random attention allocation strategy does not influence individual-level productivity, it raises the store's overall performance. We interpret this result to be caused by a significant reduction in the store's turnover costs. Indeed, a much lower attrition rate directly cuts the store's administrative and time costs on employee recruitment, training, and shift schedule change. While it takes time to talk to workers, the extra time input is worthwhile because managers are saving themselves on net by avoiding all the administrative burden related to the turnover problem. In October 2019, we interviewed several managers from the treatment group. Managers spoke highly of the firm's managerial attention strategy. For instance, one manager reflected that "*...our store has seen much fewer attrition cases during the previous months. In fact, we succeeded in retaining almost every worker for three consecutive months. You couldn't imagine how much it influenced our shift schedules. In the past, we sometimes encountered the problem of not having enough workers to serve our customers. This didn't happen even once during the last few months.*" Random allocation of managerial attention thus improves firm performance by reducing the costs from losing employees.

4.3 Average Treatment Effects on Individual Survey Outcomes

Since managers from the directed attention allocation group receive more information about employee emotional status compared to those from the random attention group, this information could be useful for improving the efficiency of communication. A natural question to ask is whether managerial attention helps improve the well-being of employees. To answer this question, we look at the impact of different

attention allocation strategies on employees' survey outcomes.

Table 5 uses both pre- and post-treatment employee survey data to analyze the impact of managerial attention on employee job satisfaction, evaluation of bosses, stress level, and mental health conditions. Column 1 suggests that both directed and random attention positively influence job satisfaction: the intervention raises employee job satisfaction by 0.19 and 0.10 standard deviations respectively. The directed attention allocation strategy has a larger effect on job satisfaction compared to the random allocation strategy. Column 2 shows that directed and random attention allocation strategies improve workers' evaluation of bosses by 0.14 and 0.22 standard deviations, respectively. Both coefficients are statistically significant at the 1% level. Columns 3 and 4 show that workers from the directed attention group have reduced their stress levels and improved their mental health conditions by 0.11 and 0.13 standard deviations. In contrast, workers in the random attention group feel no different from those in the control group in terms of average stress levels and mental health conditions.

Taken together, the results suggest that information from high-frequency survey data helps target those who might need more attention and care. Compared to the random attention group, workers from the directed attention group improve more significantly in their job satisfaction, stress level, and mental health condition. However, the random attention allocation strategy raises employee's evaluation of their managers by a larger margin. There are two findings of note. First, more information on workers does improve manager-worker communication efficiency. When a worker is upset, a timely conversation from the manager could be useful to help improve his mental health. Second, when a manager strategically allocates her attention, this could also influence how workers evaluate their bosses. For instance, workers might believe that the manager targets those who are unhappy or unproductive not because she cares about them, but because they impose a negative externality on team productivity. Such possibility negatively influences employee evaluations of managers and undermines the effect of managerial attention. We provide further empirical evidence of this mechanism in Section 5.1.

Finally, despite the potential side effect of strategic conversations, directed attention still has a large and significant causal impact on workers' evaluations of managers. In other words, workers prefer strategic attention to less attention from their managers. During our interviews with workers, some struggling workers expressed understanding for when their bosses only talk to them for self-serving purposes. For instance, one worker suggested that "*If my performance is bad, both my manager and I suffer. I am still happy when she comes to talk to me. After all, if she tries to help out, that is a good thing for me too.*" According to another interviewed worker, "*I feel honored when my manager talks to me despite the reasons behind. At least she thinks I am important and is worth her time.*" The variations in workers' responses, though anecdotal, corroborate the nuanced nature of attention allocation as a management practice, as contended

in the model.

4.4 Heterogeneous Treatment Effects on Attrition and Productivity

In this section, we explore heterogeneity in managerial attention effects along five pre-specified store-level observables: average employee age, store size, pre-treatment store revenue, turnover rate, and share of female employees. For all dimensions, we divide the sample into above- and below-median groups using baseline values of the heterogeneity variable. We then estimate the effect of managerial attention as a treatment on each group separately.

Table 6 reports the results for three major dependent variables: attrition, individual sales, and store revenue. Panel A explores how managerial attention influences the attrition rate. Column 1 shows that managerial attention reduces the attrition rate by 1.95 percentage points (14.9%) in stores where employees are younger on average. In contrast, the effect is much smaller in stores with older workers and is not statistically significant. Column 2 suggests that the attrition rate drops by 2.34 percentage points (17.9%) in small stores. Presumably, communication is more effective in smaller teams and the marginal effect of each conversation could be higher. Columns 3 and 4 indicate that managerial attention is more effective in stores with worse baseline performance. In particular, the intervention has a substantial influence on stores suffering attrition problems prior to the experiment: attrition rate drops by 2.90 percentage points (22.1%) and the coefficients are statistically significant at the 1% level. Column 5 shows that the attrition rate decreases by 2.10 percentage points (16.1%) in stores with larger shares of female workers.

Panels B and C provide further evidence that employee age, store size, and baseline turnover rate matter. Contrary to the finding in panel A, column 1 of panels B and C shows that managerial attention is more effective in stores with older workers, improving individual sales and store revenue by 7.8% and 12.6% respectively. The coefficient is statistically significant at the 1% level in panel C. Column 2 of panel C shows that managerial attention raises store revenues by 9.6% in smaller stores, which is well above the average treatment effect across all the stores. Column 4 shows that stores with significant turnover problems experience improved individual-level sales by 17% and store-level revenues by 8.6%. The two coefficients are statistically significant at 1% and 5% levels, respectively.

Together, the heterogeneity treatment analysis reveals three interesting patterns of how managerial attention influences worker performance. First, attention influences different parts of performance among older and younger workers. Younger workers are normally more prone to higher turnover and managerial care helps them stay. In comparison, attention helps improve old workers' productivity while leaving the turnover rate unaffected. This finding indicates that managers should employ different attention allocation strategies considering the characteristics of different groups of workers. Second, managerial attention is

particularly useful in smaller stores. This also suggests that conversation alone may be insufficient due to the more sophisticated interpersonal relationships in larger stores, wherein firms will need to align worker's incentives with more complementary management practices and incentive schemes. Third, managerial attention practice works best in stores with higher baseline turnover rates. Indeed, the marginal value of attention is lower in stores that are less concerned with turnover problems. For such stores, their baseline turnover rates are closer to the "efficient" level, and there is limited room for further improvement.

5 Mechanisms

We find that the random attention allocation strategy, compared to directed attention, is more effective in reducing the attrition rate. In this section, we discuss and provide further evidence for the underlying mechanisms. The major mechanism, we argue, is that workers make inferences about manager type and update their beliefs based on how the manager allocates her attention. A manager who allocates her attention strategically is more likely to be perceived as the selfish type who only cares about team performance or her own payoff. Such beliefs undermine not only the workers' evaluation of the manager but also the impact this attention has on the workers.

5.1 Updated Beliefs of Managers

To test this mechanism, we conducted detailed interviews with forty workers from the two treatment groups in October 2019 after the experiment. Furthermore, we conducted a novel survey experiment seven months after the RCT in April 2020. For the survey experiment, we randomly allocated 4031 respondents to two groups and presented each group with one of two versions of the survey questions about managerial attention:

Question 1

Version 1: If your manager has a conversation with you *when you are down or unproductive*, what is the major reason behind it?

Version 2: If your manager has a conversation with you *at random*, what is the major reason behind it?

Answer options (both versions): Genuinely care about me (A), Care about her own productivity (B), Unsatisfied with my performance (C), Requested by her superior (D), None of these reasons (E).

Question 2

Version 1: If your manager has a conversation with you because *she cares about the productivity of your team*, what is your evaluation of the manager?

Version 2: If your manager has a conversation with you because *she cares about you*, what is your evaluation

of the manager?

Answer options (both versions): Very low (1), Low (2), Average (3), High (4), Very high (5).

For the first question, the two versions differed only in their description of the timing of the conversations as either *when you are down or unproductive* or *at random*. We randomized the order in which the answer options were presented. For the second question, the two versions differed only in that they described the reasons for conversations as either *the manager cares about the productivity of your team* or *the manager cares about you*. For Version 1 respondents, who we refer to as the directed allocation group (T3), we measured preferences over the strategic allocation of managerial attention, whereas for Version 2 respondents, who we refer to as the random allocation group (T4), we measured preferences over the random allocation of managerial attention. Randomization ensured that the two groups of respondents were (in expectation) identical in observed characteristics that may confound comparison across groups. Table A1 displays a balance check that confirms the two groups are quite similar.

Table 7 summarizes the survey responses. Panel A reports worker perceptions of why managers talk to them. On average, about half of the respondents believe it is because managers genuinely care about them. About one-fifth of the respondents think a manager does so due to performance concerns. Very small proportions of workers chose "*unsatisfied with my performance*" or "*requested by her superior*", and about 19% chose "*none of these reasons*".[23] The answers reveal two interesting patterns. First, a higher proportion of respondents from the random allocation group (55% vs. 47%) perceive the managers to be "altruistic". Second, more workers from the directed allocation group (34% vs. 23%) believe that managers either are selfishly looking out for their own payoff or talk to them only because they are asked to do so by their superiors. While the magnitude of differences between the two groups is not very large, it is important to note that belief-updating is a recurring process. If a manager consistently allocates her attention strategically, multiple rounds of belief-updating could cause serious differences between the two groups. Panel B suggests that a manager's motive influences a worker's evaluation. When a worker knows the manager talks to him because she cares about team performance, his evaluation of the manager drops, on average, from 3.89 to 3.47. Both pieces of evidence are in line with the belief-updating mechanism.

Some anecdotes from workers in the directed allocation group provide further evidence that this mechanism is in operation such as "*sometimes I feel like a 'machine' without emotions. People always say we are family. Embracing your ideal dream, you are scratched by what is real. We are bound by our performance, and that is the only reason why people care about you.*" Another worker describes her feelings as "*a bit uncomfortable. I understand why they are doing it this way. I personally want to perform better too, but this*

[23] Among those who chose "*none of these reasons*", the reasons they gave vary widely. For example, a few deemed the action as "*not particularly intentional*" whereas a handful considered it a way "*to solicit information for better management*".

should not be just about performance." In fact, many workers understand that their manager's incentives are aligned with their own and are satisfied with managerial attention regardless of the underlying reasons. However, as workers do update their beliefs regarding manager type, it may inevitably impact the employee appraisal of manager negatively.

5.2 The Impact of Conversations on Attrition

One alternative explanation could be that the directed allocation method may not be targeting the workers that would lead to optimal impact. Since the most unhappy workers may have already made up their mind to leave, the marginal value of spending time on these workers could be small. In contrast, random allocation of attention could be more useful because preventative conversations help reduce attrition probabilities. To rule out this possibility, we assemble detailed implementation, survey, and attrition data to assess the impact of conversations on attrition.

Table 8 explores the impact of managerial conversations on attrition rate. Columns 1 and 2 assess the effect of survey scores and conversational characteristics on attrition. Column 1 shows that survey scores are strongly associated with attrition probabilities: workers with one point higher monthly average survey scores are associated with a 1.37 percentage points (10.5%) reduction in attrition rate. The result provides suggestive evidence that survey scores capture workers' emotions and mentalities and are predictive of worker turnover probability. This also rules out the possibility that strategic allocation is less effective in reducing turnover rates, because survey information is low-quality. Second, the number of conversations is negatively correlated with attrition probabilities, suggesting that more conversations may help prevent turnover. However, we do not make any causal claim for the relationship, since the number of conversations a worker may have with his manager is likely endogenous to his tenure. Furthermore, turnover rate decreases with conversation quality. Here, conversation quality is a dummy variable that equals 1 if the average conversation quality score for a worker in that month is above 1.15, and 0 otherwise.[24] The result produces suggestive evidence that higher-quality conversations lead to a lower turnover rate. Column 2 restricts the same analysis to a smaller sample of all treated stores, and exhibits the same pattern.

Given significant differences between the nuances of attention allocation strategy and conversation quality, it is natural to ask whether the timing of conversation matters. For instance, if a problem arises at work, a timely follow up from a manager may be particularly effective in persuading the worker to stay. However, if a worker is unhappy and the manager fails to address his problem, this might instead increase his probability of quitting. Columns 3 and 4 restrict the analysis to only workers experiencing

[24]Each interview log is graded by a graduate research assistant (RA) for quality control15 according to four different scales: excellent (1.25), OK (1), poor (0.8), implementation failure (0). On average, managers held about 8.4 weekly conversations in each store and the mean conversation quality score is above 1.1. See Figure 4 for patterns in the raw data.

bad emotional conditions.[25] We construct a variable of "timely conversation" by combining the survey and implementation data. Since we document both the trajectory of individual survey scores and the timing of each conversation, we observe whether a manager happens to talk to a worker right after he is upset. "Timely conversation" is coded as 1 if a manager has a conversation with the worker within two weeks after he is upset and 0 otherwise.[26] Column 3 shows that having a timely conversation significantly reduces probability of quitting by 3.39 percentage points (25.9%). Column 4 restricts the analysis to the treated stores and finds that timely conversations lower the turnover rate by 4.96 percentage points (37.9%). Together, the results suggest that conversations have a substantial effect on workers with bad emotions, ruling out the possibility that the directed attention strategy did not target the correct group of employees.

5.3 Other Mechanisms

There is little support for several other alternative mechanisms.

Managers feel motivated because they know they are being watched. The results are unlikely to be driven by the Hawthorne effects. First, none of the managers knew about the RCT or how the list was generated. Second, Hawthorne effects cannot explain the difference between the two treatment groups because any Hawthorne effects should cancel out. Third, attention allocation is just one of the manager's hundreds of routine tasks, and managers are unlikely to pay special attention to this task.

Managers from the two treatment groups have a different use of their time during the implementation stage. The design of the experiment rules out this possibility, because we hold the manager's time input fixed across the two treatment groups. Since managers talk to the same number of workers, and conversations are standardized, different time use is thus a consequence, rather than the cause of the store's lower attrition rate.

Control store frustration. Evidence works against this interpretation. First, none of the control stores knew about this policy in treatment group stores. We asked control store managers whether they heard of any policies in a nearby treatment store regarding managerial attention after the experiment through survey questions. No managers were aware of the existence of such a policy. Second, we asked both the HR and operations department to record complaints during the RCT, but no such complaints were registered.

Managerial attention helps stores improve hiring decisions. Perhaps our policies help managers learn more about the different types of workers and this knowledge may help them recruit workers that are better suited to the store and its position(s). Table A2 finds no evidence that treatment stores recruited workers with different characteristics during the experiment, so this potential mechanism is unlikely to

[25] Observations are at the worker-month level, and we focus on observations with below-median survey scores.

[26] We also use an alternative method coding "Timely conversation" as 1 if a manager has a conversation with the worker within one week after he is upset and the result is consistent.

hold.

6 Conclusion

While a growing body of literature has examined the impact of managers on employee performance, the manner in which managers should allocate their limited attention among workers remains largely unknown. Drawing on a large-scale 6-month randomized control trial at a leading multi-national spa chain with over 10,000 workers, this paper is the first study to provide theoretical and experimental evidence on the effects of different managerial attention allocation strategies on worker attrition, productivity, well-being, and firm performance.

We compare the random allocation method, where attention allocation is uncorrelated with any employee characteristics, to the directed allocation method, where managers strategically focus on workers with potentially higher attrition probabilities. Consistent with our theoretical prediction, we find random allocation to be more effective: employee attrition drops by 13.9% and store revenues increase by 6.6% relative to the control group, with the directed attention group experiencing considerably smaller, statistically insignificant effects. Workers from the treatment groups also report substantially higher job satisfaction, evaluation of managers, less work stress, and better mental health. Based on both theoretical, empirical, and qualitative evidence, we show that random allocation is more effective because workers care about managers' motives behind these conversations and update their beliefs of managers' types accordingly. Strategic allocation of attention can actually backfire because workers are more likely to believe the manager is a "selfish type".

This experiment highlights an interesting trade-off between the rising communication efficiency and the declining probabilities of being perceived as altruistic, both due to having more information on employee emotions. Therefore, the overall impact depends on the joint effects shaped by both forces. The takeaway from this study is not that strategically allocating managerial resources always yields sub-optimal outcomes in any firm. Indeed, the impacts of managerial practices are complementary to many factors such as worker characteristics, work environment, and organizational culture, and the optimal managerial resource allocation strategies could be context-dependent. Instead, we provide existential proof of the potential backlash of the strategic use of information. Managers should take into account the potential downsides of being "too strategic" when deciding how to effectively allocate their limited attention among workers to improve both worker well-being and firm profitability.

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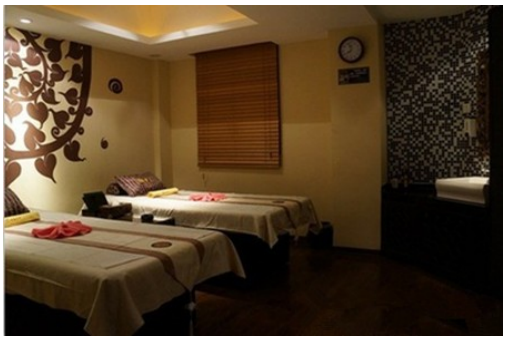
Figures & Tables

(a) Store lobby



(b) Spa room

(c) Service

(d) Speech to store managers during corporate annual conference

Figure 1: The company is the largest multinational spa chain, headquartered in China, with more than 500 stores worldwide.

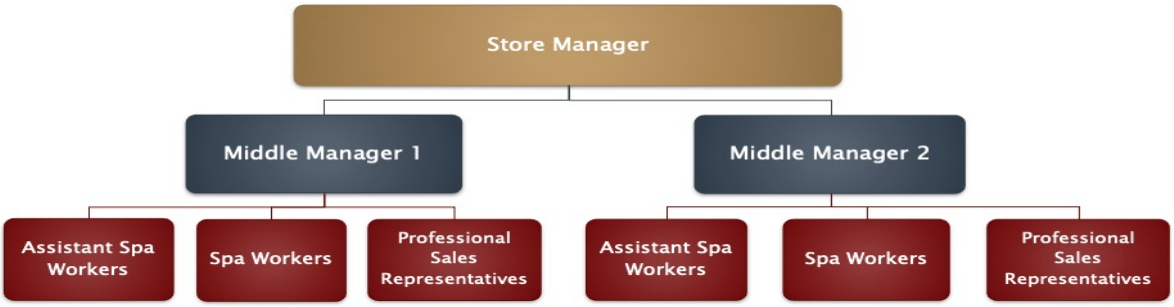


Figure 2: Organizational chart within a store

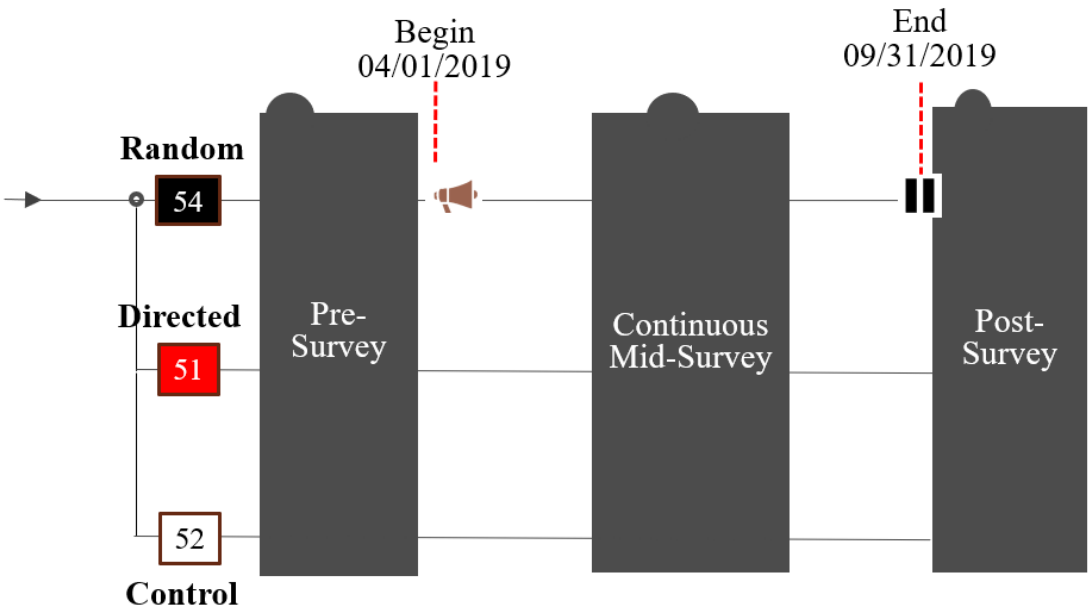


Figure 3: RCT timeline

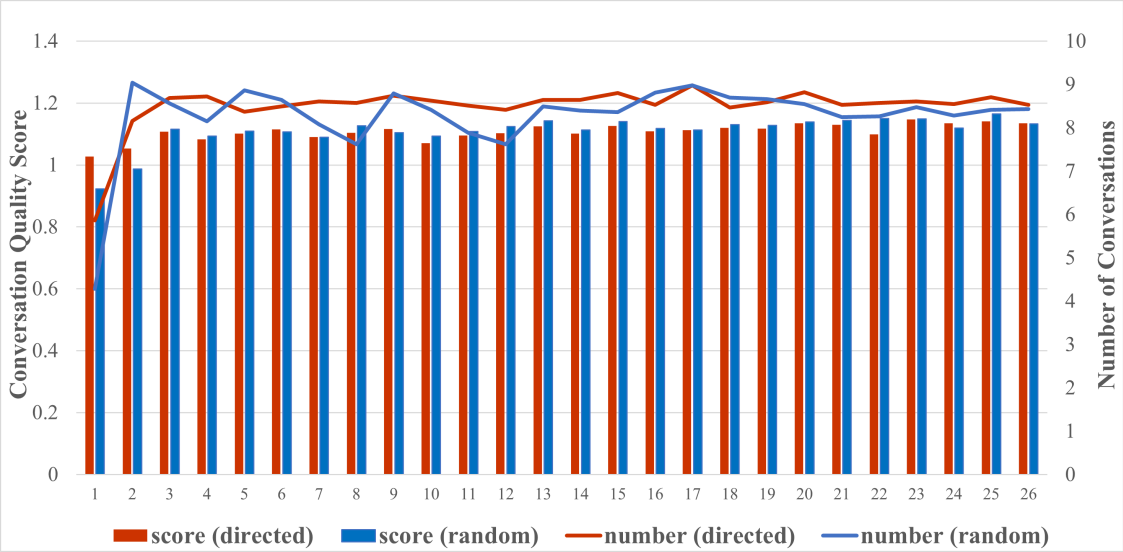


Figure 4: Number and quality of conversations by month (N=22,822)

Table 1: Comparing Pre-Treatment Store Means across Different Groups (N=157): Randomization Check

	Comparing All 3 Arms				Treatment vs. Control	
	Control	Directed	Random	p-val	Treatment	p-val
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Store Characteristics						
Revenue in 1000 RMB	629.86***	-20.99	9.99	0.96	-5.06	0.96
	(74.97)	(106.54)	(105.04)		(91.40)	
Monthly revenue (log)	13.12***	-0.02	0.02	0.96	0.000	0.99
	(0.09)	(0.13)	(0.13)		(0.11)	
Store size (sq meters)	1199.10***	-100.77	-58.76	0.66	-79.16	0.41
	(77.80)	(110.56)	(109.00)		(94.87)	
Store history (years)	4.31***	1.04	-0.02	0.41	0.49	0.53
	(0.64)	(0.90)	(0.89)		(0.78)	
Monthly turnover	13.15***	0.31	0.66	0.80	0.49	0.57
	(0.70)	(1.00)	(0.99)		(0.86)	
Location (city)	0.79***	0.02	0.03	0.94	0.02	0.76
	(0.06)	(0.08)	(0.84)		(0.07)	
Panel B. Employee Characteristics						
No. of Employees	42.52***	-0.15	1.02	0.95	0.45	0.89
	(2.77)	(3.93)	(3.88)		(3.37)	
Age	32.06***	0.46	0.70	0.15	0.58*	0.07
	(0.26)	(0.37)	(0.36)		(0.32)	
No. of spa workers	27.46***	-0.21	1.71	0.72	0.77	0.74
	(1.84)	(2.61)	(2.59)		(2.25)	
Male employee	34.87***	0.43	0.78	0.90	0.61	0.68
	(1.22)	(1.73)	(1.71)		(1.49)	
No. of managers	2.10***	0.18	0.29	0.41	0.24	0.22
	(0.16)	(0.22)	(0.22)		(0.19)	
Male store manager	0.94***	-0.00	-0.03	0.73	-0.02	0.67
	(0.04)	(0.05)	(0.05)		(0.04)	

Notes: The table compares pre-RCT store-level characteristics for the control group, directed treatment, and random treatment. The pre-RCT period is from July 2017 to January 2019. ***p<0.01, **p<0.05, *p<0.1

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

Estimators	Attrition			
	Treatment vs. Control		DID	
	(1)	(2)	(3)	(4)
Directed	-0.807			
	(0.713)			
Random	-1.606**			
	(0.735)			
Directed × Post			-1.034	
			(1.200)	
Random × Post			-1.816**	
			(0.858)	
Treatment		-1.255**		
		(0.640)		
Treatment × Post				-1.446*
				(0.805)
Month fixed effects	✓	✓	✓	✓
Store fixed effects	✗	✗	✓	✓
Mean DV if Treatment=0	13.07	13.07	13.07	13.07
Number of observations	26394	26394	107009	107009

Notes: Columns 1-4 are linear probability models, where the dependent variable is whether an employee attrites in a month. The coefficients are multiplied by 100 for readability. An observation is a worker-month. Columns 1-2 use the experimental data during the RCT (April-September 2019). Columns 3-4 include both pre-RCT and RCT data from January 2018 to September 2019. Controls include individual characteristics (age, gender, prior work experience, marital status) and store characteristics (whether the store is in a city, years of operation, pre-RCT average monthly revenue, pre-RCT average monthly turnover rate, number of employees, and share of female employees). Robust standard errors are clustered at the store level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3: Average Treatment Effects on Individual Labor Supply and Productivity

Dependent variables:	Attendance	Returning customer share	log (sales)	log (compensation)
	(1)	(2)	(3)	(4)
Directed × Post	-0.187	0.158	-0.069	-0.030
	(0.325)	(0.217)	(0.043)	(0.020)
Random × Post	-0.037	0.005	-0.008	0.007
	(0.287)	(0.012)	(0.041)	(0.020)
Month fixed effects	✓	✓	✓	✓
Store fixed effects	✓	✓	✓	✓
Mean DV if Treatment=0	24.33	0.30	9.57	8.89
Number of observations	105639	85230	97715	105943

Notes: The table shows the average treatment effects on attendance and productivity. Observations are at the worker-month level. Controls are the same as in Table 2. Robust standard errors are clustered at the store level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Table 4: Average Treatment Effects on Store-level Performance and Productivity

Dependent variables:	log (store revenue)	log (No. of customers)
	(1)	(2)
Directed × Post	0.001	-0.030
	(0.047)	(0.086)
Random × Post	0.066**	-0.104
	(0.030)	(0.092)
Month fixed effects	✓	✓
Region fixed effects	✓	✓
Mean DV if Treatment=0	13.21	7.60
Number of observations	1413	1413

Notes: The table reports the average treatment effects of managerial attention on store-level performance using data from January to September 2019. Observations are at the store-month level. The dependent variables are the log of store revenue and the log of store customers. Control variables include store-level characteristics (whether the store is in a city, pre-RCT monthly turnover rate, pre-RCT monthly sales, the number of store employees, average employee age, and the share of female employees) and a manager change dummy. Robust standard errors are clustered at the region level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 5: Average Treatment Effects on Individual Survey Outcome

Dependent variables:	Job satisfaction	Manager evaluation	Less stress	Mental health
	(1)	(2)	(3)	(4)
Directed × Post	0.194***	0.141***	0.109**	0.133**
	(0.048)	(0.049)	(0.049)	(0.046)
Random × Post	0.103**	0.221***	0.059	-0.007
	(0.049)	(0.047)	(0.052)	(0.048)
Store fixed effects	✓	✓	✓	✓
Mean DV if Treatment=0	3.84	3.98	2.94	3.51
Number of observations	73385	47063	48199	45288

Notes: The table shows the average treatment effects on individual-level job satisfaction, evaluation of managers, stress level, and mental health. Observations are at the worker-day level. Controls are the same as in Table 2. Robust standard errors are clustered at store level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 6: Heterogeneous Treatment Effects on Attrition and Productivity: April 2019-September 2019

	Employee Age	Store Size	Store Revenue	Turnover Rate	Female Share
	(1)	(2)	(3)	(4)	(5)
Panel A: Attrition (×100)					
Above median	-0.642	-1.137	-0.651	-2.895***	-2.101*
	(1.262)	(1.007)	(0.959)	(1.028)	(1.128)
Below median	-1.952*	-2.338**	-1.704	-0.269	-0.885
	(1.033)	(1.106)	(1.050)	(0.927)	(1.225)
p-val,diff	(0.050)**	(0.550)	(0.707)	(0.034)**	(0.445)
Observations	26467	26467	26467	26467	26467
Panel B: Log Sales					
Above median	0.078	0.031	0.035	0.157***	0.003
	(0.059)	(0.078)	(0.082)	(0.057)	(0.089)
Below median	-0.027	0.051	0.037	-0.054	0.093
	(0.099)	(0.058)	(0.060)	(0.079)	(0.074)
p-val,diff	(0.498)	(0.850)	(0.948)	(0.027)**	(0.580)
Observations	26140	26140	26140	26140	26140
Panel C: Log Store Revenue					
Above median	0.126***	0.021	0.129	0.086**	0.046
	(0.037)	(0.035)	(0.073)	(0.036)	(0.061)
Below median	0.057	0.096**	0.055	-0.009	0.096**
	(0.049)	(0.044)	(0.050)	(0.041)	(0.036)
p-val,diff	(0.231)	(0.675)	(0.108)	(0.086)*	(0.756)
Observations	942	942	942	942	942

Notes: The table reports OLS estimates of the heterogeneous treatment effects on the major outcome variables. Each dimension of heterogeneity is indicated at the top of the table. In each panel, the "Above median" row reports the effects for the subgroup with above-median baseline values of the heterogeneity variable. ***p<0.01, **p<0.05, *p<0.1

Table 7: The Impact of Manager Motives on Employee Beliefs and Evaluation

Reason	Directed Allocation N=1938	Random Allocation N=2093
Panel A: Employee perceptions of the conversation reasons		
"Genuinely care about me"	47.00%	54.95%
"Care about her own productivity"	26.74%	18.06%
"Unsatisfied with my performance "	3.10%	2.81%
"Requested by her superior "	7.61%	4.44%
"None of these reasons"	19.10%	19.70%
Panel B: Evaluations for managers		
Mean score (1-5 scale)	3.47	3.89

Notes: The results are from our second survey experiment on 4,031 workers in April 2020. The workers were randomly divided into a directed or random allocation group. For Panel A, workers were asked "If your manager has a conversation with you when you are down or unproductive/at random, what is the major reason behind it?" For Panel B, workers were asked "If your manager has a conversation with you because she cares about her personal productivity/you, what do you think about the manager?". Question 2 uses a 1 through 5 scale, where a higher score indicates a higher evaluation of managers.

Table 8: The Effect of Managerial Attention on Attrition (Linear Probability Models)

	Attrition			
Type of workers	All	Treatment stores	All	Treatment stores
	(1)	(2)	(3)	(4)
Survey scores	-1.367***	-1.547***	-5.258***	-6.454***
	(0.384)	(0.522)	(0.813)	(1.113)
No. of conversations	-4.678***	-4.766***	-4.977***	-4.992***
	(0.355)	(0.360)	(0.509)	(0.515)
Conversation quality	-1.786***	-1.798***		
	(0.628)	(0.632)		
Timely conversation			-3.391*	-4.956**
			(1.853)	(2.027)
Month fixed effects	✓	✓	✓	✓
Store fixed effects	✓	✓	✓	✓
Number of observations	26894	18238	14142	9365

Notes: The table shows the treatment effects of managerial conversations on employee attrition during the experimental period (April 2019 to September 2019). The dependent variable is whether an employee attrites in a month and the coefficients are multiplied by 100 for readability. Observations are at the worker-month level. All the regression models control for month fixed effects and store fixed effects. Columns 3 and 4 focus on unhappy workers specifically. Robust standard errors are clustered at the store level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Online Appendix: Not for publication.

Interview Log

Information

Interviewee: Store: Gender: ☐ Male / ☐ Female

Interviewer: Time of Interview: (Month & Day)

How many times have you interviewed this employee? ---( )

Purpose of Interview

Our company's workers belong to emotional labor. Many of them lack care and attention from their managers. This interview aims to improve the work, life and emotional status of employees through one-on-one communication between managers and employees, reduce the work and emotional stress of employees, and enhance mutual understanding and support between management and employees. Let us take good care of our employees and bring everyone closer in a relaxed and trusting work environment.

Steps

Step 1. Describe the status of the employee in recent days (Recently, I observe that you look ____ in life...)

Recent changes in the employee's status: (check in the Box)

☐active and excited ☐cautious ☐consistent, no obvious change

☐emotionally unstable ☐exhausted, depressed ☐other ( )

additional inquiry: seek employees' opinions (...do you feel the same way, what is the difference?)

take down the key points:

Step 2. Summarize employee's response and ask about the recent events affecting her

(... From your personal feelings, what leads to this change/emotion, would you like to talk to me about it?)

Factors mentioned by the employee: (check in the box)

☐family ☐work ☐team and colleagues

☐relationship ☐personal reasons ☐other ( )

additional enquiry: How do you think about this matter, can you talk about it specifically?

take down the key points:

Step 3. According to the events and reasons mentioned by the employee, please pick 2 to 3 questions from the talk-to-me toolbox to have an indepth conversation

Note: At the end of each topic, please summarize the key points. Use the proper tone and wording

Summary: ... I can feel...; I tend to understand... I am very happy to know more about your life, I...

Step 4. Summarize the above conversation, make employees feel being cared and take down relevant points

Summary: …time is up. I am very happy to talk to you. I will often find chances to communicate with you…

take down 3 key points: 1.

2.

3.

Figure A1: Interview log templates used by managers

Talk-to-me Toolbox

Notes for interviewers:
1. If this is your first conversation with an employee, please note that you are an ordinary interviewer. Think about yourself as a friend, not a manager.
2. Pay attention to what the interviewees say. Try to avoid using vocabulary such as “I think”, “you should”, and “why”.
3. Learn to express your opinion in another way, such as: “I can understand your feelings...”, “What caused you to make this change, can you talk about it specifically?”
4. You can express your own opinions, please be careful not to make long speeches.
5. Interviewing principles: be respectful and sincere, listening, keep the conversation content confidential.
6. Please keep this interview within 15-20 minutes.
7. The questions below are just example questions. Certain questions might not be appropriate for some employees or under certain contexts. Feel free to bring up other appropriate topics/questions to keep the conversation going.

Please choose two to three questions under a topic for an in-depth conversation each time.
Note: At the end of every topic, you need to make a short summary and pay attention to your tone and wording.

Family I
(1) Where is your hometown? Can you tell me what your home/hometown is like?
(2) When did you contact your family recently? What topics do you like chatting with them?
(3) How is your father/mother’s health? What kind of people are they?
(4) Do you have any brothers or sisters at home? What do they do?
(5) Who do you get along well with at home? Why?
(6) What expectations do your family have for you?

Family II
(1) Has there been any change in your family recently?
(2) Did any relatives and friends come to visit you?
(3) Do you have any children? How old are they? How are they doing?
(4) Are they (your children) going to school? Where do they go to school?
(5) How is the family atmosphere? Who does the child get along well with?
(6) What is the happiest thing to do at home? Is there anything unhappy?
(7) Have you encountered any difficulties at home recently? How did you solve it?
(8) Do you have plans to buy a house? When do you plan to buy it?
(9) Where do you live? Are you far from the company? How do you usually come to work?

Work
(1) Are you used to your current job? Is there any problem?
(2) What is the most difficult part of the job? Has it been resolved?
(3) How is your work these days? Have you been wronged?
(4) Have you participated in...training? What are the gains? Did you talk to your colleagues lately? What kind of programs or events do you want the company to organize?
(5) Do you have any new work plans?
(6) Do you have any suggestions about how we could improve the working environment, conditions, and management methods?

Figure A2: Talk-to-me toolbox used by managers (Part I)

Warm Tips: During the interview, listening and looking into the eyes can increase mutual trust.

Team
(1) Have you ever thought of our team hanging out? Could you recommend a good place?
(2) How often do you think our team should hang out?
(3) How well do you get along with other people on our team? Are you used to it? How do you feel about our store?
(4) Who do you feel most impressed with in our store?
(5) Could you get help from the coworkers when you have questions?

Life I
(1) Are you satisfied with your life? What have you been up to lately?
(2) Do you have any pressure? What is it about? Do you have any troubles?
(3) Where do you live now? How is the living environment? How are you getting along with everyone in your apartment?
(4) What games do you like playing? What are your hobbies?
(5) What do you like doing when you are not at work?
(6) Did you go shopping when you are off work? Where have you been?

Life II
(1) Do you have a boy/girlfriend? Where are they from? How long have you been together? How did you meet? What do you admire most about him/her? What are your plans?
(2) What shows/TV series/movies do you like recently?
(3) Which rock star do you like the most? Why do you like him/her?
(4) Do you like listening to music? What kind of songs do you like?
(5) Which sports do you usually like? Have you followed any games recently?
(6) Do you play video games? What kind of games do you like?

Miscellaneous
(1) What kind of food do you like for meals? Are you used to the work meals? Any good suggestions?
(2) Do you sleep well? How is your health?
(3) What activities do you hope the company could organize?
(4) Your birthday is coming soon, how did you spend your birthdays? Do you have any plans for this birthday?
(5) Do you have much pressure recently?
(6) Is there any place you wish to visit?
(7) What do you like doing outside of work?

Others
What topics are you currently interested in, could you talk to me about it?

Warm Tips: Nodding and smiling help interviewees feel better.

Figure A3: Talk-to-me toolbox used by managers (Part II)

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 to or helped family or friends to get a job in 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 solving problems when you need them?
	Willing to turn to	If you have troubles, how willing are you to reach out to your managers for help?
	Leave	If you ask for leave when it is really necessary, how easy is it for you to get approval from managers?
	Fairness	How fair do you think your manager is?
Pressure	Pressure	How much pressure do you have for the job?
Mental Health	Optimism	I've been feeling optimistic about the future
	Useful	I've been feeling useful
	Exhaustion	I've been feeling relaxed
	Energy	I've been feeling interested in other people and had 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

Figure A4: Survey questions pre- and post-RCT

Table A1: Comparison of Survey Experiment Subjects

	Directed (T3)	Random (T4)	Diff: T3 versus T4	p-val
Age	33.87	34.12	-0.25	0.37
	(8.71)	(8.58)		
Female	0.75	0.75	0.00	0.84
	(0.44)	(0.43)		
Race (minority %)	0.06	0.06	0.01	0.35
	(0.24)	(0.23)		
Schooling (years)	10.49	10.41	0.08	0.27
	(2.26)	(2.34)		
Marital Status (years)	0.54	0.55	-0.01	0.60
	(0.50)	(0.50)		
Number of Respondents	1938	2093		

Note: Standard deviations are in parentheses. Column 5 reports the p-values of the two-sided t-test of equality of means.

Table A2: Average Treatment Effects on Employee Recruitment

	Age	Female	Ethnic minority	Married	Schooling	Work experience
Directed	0.114	-0.005	-0.003	-0.019	-0.171	0.285
	(0.398)	(0.026)	(0.019)	(0.027)	(0.152)	(0.434)
Random	0.324	0.008	-0.003	0.032	-0.075	0.399
	(0.384)	(0.023)	(0.013)	(0.027)	(0.151)	(0.442)
Mean in Controls	31.62	0.74	0.06	0.44	10.96	14.66
Observations	3821	3821	3821	3821	3821	3821

Note: This table compares age, gender, ethnicity, marital status, schooling, and prior work experience among hires from the treatment and control group stores. Observations are at the worker level in all regressions, and robust standard errors (clustered at the store level) are included in parentheses. ***p<0.01, **p<0.05, *p<0.1