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Abstract

Training investments are essential for improving worker and firm productivity, yet their implementation is often hindered by low participation rates and insufficient worker engagement. This study uses data from three firms–a car manufacturer, a quick-service restaurant chain, and a retail company–to show that variation in training participation among employees is closely tied to differences in middle managers' behavior and practices. Middle managers who actively engage with their employees and emphasize their well-being and development are associated with significantly higher participation in training programs. These managerial differences significantly influence employee performance and absenteeism, especially during periods of organizational change. Together, these findings underscore the importance of middle managers in bridging the gap between centrally designed HR policies and their effective on-the-ground execution.

Keywords: Training, Productivity, Absenteeism, Middle Managers
JEL: J24, M12, M53, L23

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1 Introduction

Training is broadly recognized as essential for improving workers' skills and productivity, firm performance and economic growth (Adhvaryu et al., 2023c,d; Bartel, 1994, 1995; Becker, 1964; Dearden et al., 2006; Espinosa and Stanton, 2022; Konings and Vanormelingen, 2015). Existing research has largely emphasized the role of labor market imperfections in shaping firms' training investments (Acemoglu and Pischke, 1999; Leuven, 2005). In contrast, far less attention has been devoted to understanding the organizational frictions that may hamper the implementation of training programs within firms.[1] Recent evidence suggests these frictions are nontrivial: despite substantial investments, firms often struggle to implement training programs effectively. Participation rates remain low, and workers' engagement is often inconsistent, undermining the potential returns on these investments.[2] Overcoming these internal constraints is key to enhancing training program effectiveness and shaping policies that encourage firms' investment in human capital.

This paper addresses the gap in the literature by examining how middle managers facilitate—or hinder—the execution of centrally designed training programs. Using detailed administrative data from three large firms in Latin America—a car manufacturer, a quick service restaurant chain, and a retail company—we document substantial heterogeneity in training take-up among employees working in similar roles. Second, we show that this variation is closely tied to differences in middle managers' behavior and practices: middle managers who actively engage with their employees and emphasize their well-being and development foster significantly higher participation in training programs. Third, these managerial differences strongly influence employee performance and absenteeism, particularly during times of organizational change.

These findings have implications for both policy and practice. Public policy frequently relies on training subsidies or tax incentives to spur workforce development (Dillon et al., 2024). However, these policies often assume that once a firm receives the subsidy, training is automatically implemented. Our results uncover a previously overlooked friction—namely, that mid-level managerial support (or lack thereof) can substantially impede or amplify the actual take-up of firm-specific training. In so doing, we highlight an important channel through which policy-induced training initiatives may fail to translate into skill acquisition, productivity improvements, and wage growth.[3] Similarly, by demonstrating the critical role of middle managers in training implementation,

[1] Bartel (1995) and Krueger and Rouse (1998) leverage firm-level data to study the impact of training on workers' wages and performance. However, they do not explicitly study frictions in training implementation within the firm. See Black et al. (2023) for an excellent review on the literature on firm training.

[2] Leuven and Oosterbeek (2008) highlight low participation rates in voluntary training programs, while Barron et al. (1997) discuss difficulties in measuring training effectiveness. Sandvik et al. (2021) find that voluntary training programs attract the best employees, who benefit the least from it. Tamayo et al. (2023) discuss organizational frictions in the implementation of reskilling investments inside firms drawing from qualitative interviews.

[3] This relates to the observation made in Gibbons (2010) that organizational frictions may "cause organizations to respond to policy initiatives differently than would be predicted from the assumption that firms costlessly and constantly

we highlight the need for firms to incorporate managerial incentives and practices into the design of training programs.[4] More broadly, these findings suggest that training relies on complementary managerial practices and behaviors.[5]

The three firms in our study are an Argentinian car manufacturer with approximately 1,800 employees, a quick service restaurant chain with 2,500 employees, and a large retail company with 25,400 employees, both based in Colombia. For each of these firms, we leverage rich administrative data that allow us to track employee training participation, program types, and manager-employee reporting relationships. The data also provide information on performance at the team level, as well as detailed HR outcomes such as employees' absenteeism and turnover.

We focus our analysis on firm-specific training programs, which are centrally designed by the HR department to foster the development of operational skills among front line workers. Each firm compensates workers for time spent in training, but does not offer direct financial incentives for acquiring firm-specific skills. Instead, they align incentives by positioning training as essential for career progression and promotion eligibility. Despite these incentives, training participation remains low and varies significantly across units.

As in many organizations, middle managers in our study do not actively implement training programs. Instead, each firm employs specialist trainers, and middle managers receive no direct compensation based on their employees' participation in training.[6] In our interactions with the firms, however, we realized that in practice, middle managers could still affect training decisions in other ways: positively, by recommending specific programs or clarifying the potential career benefits of skills acquisition to their direct reports, or negatively, demonstrating skepticism to the idea that employees should spend time in training rather than working on the shop floor. Consistently with this notion, we find that differences in training take-up rates across teams within the same firm can be largely accounted for by the identity of the middle manager assigned to the team. Leveraging the exogenous rotation of managers across teams, we observe substantial variation in middle managers' contributions to training take-up. Using an event study design, we show that the arrival of a High Training (HT) manager—defined as a manager who is above the company median in terms of training value added—leads to a large increase in training take up among employees: within the first 8-weeks of an HT manager's arrival, take up increases by 45% for the car manufacturing firm, 55% for the quick service restaurant chain and 60% for the retailer.

Thanks to auxiliary survey data self-reported by the managers, we show that HT managers are

optimize their choices from a fixed and known production possibility set."

[4]In a recent paper, Friebel and Raith (2022) discuss incentive schemes that explicitly reward middle managers for developmental activities and prevent talent hoarding (Haegele, 2022).

[5]See Barron et al. (1997) for an early discussion of this point.

[6]Middle managers have to certify whether participants have acquired the desired skills after training, but this activity is not compensated.

sharply distinct from others in terms of some personal characteristics—in particular, their social skills and extroversion—and people-related management practices. Namely, they are more likely to involve their employees in decision-making, engage in retrospective learning, focus their attention on weak performers in their teams, and care about workers' engagement and well-being.

These findings underscore the pivotal role of middle managers in translating central HR policies and career opportunities to frontline workers, even if this role is not explicitly recognized in their compensation. Furthermore, influencing training participation is part of a broader managerial approach that prioritizes team well-being and professional development. Consistently with this interpretation, we show that HT managers are different also in terms of other HR-related outcomes: their teams have lower levels of absenteeism and turnover, and higher promotion rates.

We find that HT managers are generally more productive, and their teams adapt more effectively to production process changes following a sudden positive demand shock, even without differential compensation for the extra effort.[7] This exogenous shift in labor demand is akin to a forced (and uncompensated) increase in workers' effort—an ideal setting to test whether HT managers (who may more easily reassign jobs or engage workers in multi-tasking) help buffer the shock. We find that, after the demand shock, workers reporting to HT managers produce more, and are much less likely to engage in absenteeism. We exploit the richness of the data to show that the difference between HT and LT managers in absenteeism is more pronounced among workers and occupations more likely to be affected by the changes in production, and for workers who face better outside options at the onset of these changes (i.e., those facing a lower unemployment rate in the area surrounding their workplace). Finally, using a setup similar to Bandiera et al. (2018), we show that teams reporting to HT managers are also less responsive to a weather shock—a sudden and large increase in rainfall in the vicinity of the workplace—that increased workers' cost of effort. In the last part of the empirical analysis, we show that the effect of HT managers on workers' absenteeism does not merely reflect workers' skills or managerial attitudes. Rather, HT managers appear to manage the shock differently from others, fostering training and proactively promoting workers as the shock unfolds. We interpret these results as evidence that local managers who previously encouraged skill acquisition effectively "coordinate" their teams during shocks.

We conclude the paper with a stylized model in the spirit of Prendergast (1993). Our contribution is to augment a classic moral-hazard training framework with the notion that promotions—and thus wage returns—are credible only if frontline managers effectively convey and honor them. The model assumes that middle managers differ in their ability to amplify or dampen the effects of centralized wage policies designed to incentivize sorting into training or, more specifically,

[7] In the car company this consists of two centrally imposed production expansions (approximately 27% and 38%) determined by the CHQ, while for the retailer and quick service restaurant chain we study the staggered roll-out across stores of a partnership with a last-mile delivery service that increased transactions by 3% and 6%, respectively.

into “difficult” jobs that require specialized skills. This implies that heterogeneity in “managerial type” can lead to large within-firm variance in training uptake, well beyond what the formal wage schedule suggests. We embed this heterogeneity within a labor supply framework coupled with the firm’s profit optimization process, deriving comparative statics to analyze the impact of a shock that increases the value of trained workers in production, to mimic the organizational changes we examine in the empirical analysis of the demand shock. The model shows that, in the long run, such a shock would prompt the firm to raise the relative wage premium for jobs requiring training to incentivize take-up. However, in the short run, when wages are fixed, the firm accommodates the shock by attempting to extract more effort from existing workers, pushing them beyond their optimal labor supply. In line with our empirical findings, the model predicts that, if wages are constant, workers will be more likely to engage in absenteeism to move closer to their optimal labor supply. Importantly, the model also predicts that the absenteeism response is attenuated in units led by HT managers. This is because teams reporting to HT managers have higher baseline trained workers (who are better compensated), and even their untrained workers are more likely to anticipate future wage adjustments or promotions, so that they sort into training even before the wage increase materializes.

The study builds on previous research on training and productivity (Adhvaryu et al., 2023c,d; Bartel, 1994, 1995; Dearden et al., 2006; Espinosa and Stanton, 2022; Konings and Vanormelingen, 2015). It complements prior work that explored the impact of training on individual wages by focusing on the firm-level outcomes of training investments. Compared to existing studies, this paper can leverage much more granular and longitudinal data on both training programs and take-up, highlighting the importance of within-firm variation in evaluating training effectiveness.

Additionally, the paper contributes to the literature on management practices and firm performance (Adhvaryu et al., 2023e; Bloom et al., 2014, 2012; Bloom and Van Reenen, 2010; Friebel et al., 2023; Hoffman and Tadelis, 2021; Metcalfe et al., 2023; Minni, 2024), showing that the implementation of centralized HR policies is mediated by the actions of middle managers. This result is in line with the findings emerging in the literature dedicated to middle managers in personnel and organizational economics (Adhvaryu et al., 2021, 2022; Frederiksen et al., 2020; Friebel et al., 2023, 2022; Hoffman and Tadelis, 2021; Lazear et al., 2015; Metcalfe et al., 2023). Our findings are closely related to work by Hoffman and Tadelis (2021) and Minni (2024), who find that middle managers have a large influence on workers’ outcomes, such as retention and career progression. The contribution of this paper relative to the existing literature in this area is to show that the value of middle managers extends to the implementation of firm-sponsored training programs, thus establishing a novel link between manager type and workforce skill accumulation. We also show the performance implication of managerial attitudes in relation to a large demand shock.

The paper also contributes to the literature on “insider econometrics” (Ichniowski and Shaw,

2003) by leveraging rich personnel data and methods in exactly the same way across three organizations operating in three different sectors and settings. By doing so, the paper attempts to provide some generality to the basic finding that middle managers matter for training implementation.

Finally, our paper contributes to the literature studying relational contracts within firms (Adhvaryu et al., 2024; Gibbons and Henderson, 2012a,b), particularly focusing on how human capital investments can foster cooperation among teams (e.g., firm-worker relationships) (Carmichael and MacLeod, 1997; Teodorovicz et al., 2024). Our research complements this by showing how middle managers' engagement in promoting employee professional development can significantly enhance participation in training programs, thereby affecting productivity and reducing absenteeism.

The paper is structured as follows. Section 2 presents the firms included in the study, while Section 3 shows the data and summary statistics. Section 4 discusses the estimation of managerial fixed effects in training, while Section 5 presents the results related to the role of HT managers for performance. Section 6 describes the model and Section 7 concludes.

2 Context

The three firms included in the study are a car manufacturer in Argentina, a quick service restaurant chain, and a large retail company, both based in Colombia. The three companies are all large subsidiaries of multinational firms. In what follows, we describe their main production activities, their organizational structure, including the role of middle managers, their training programs, and the demand shocks that we leverage to estimate the importance of middle managers for firm performance. Table A.1 provides a summary of the three companies.

2.1 Activities

Car Manufacturer The car manufacturer is the Argentinian subsidiary of a global company that produces a wide range of automotive models. The firm operates an assembly plant in Argentina and employs approximately 1,800 workers. Production takes place in a structured production line setting, consisting of eight sectors: Press, Welding, Painting, Frame & RX Axle, Engines, Resin, Assembly, and Quality Check.[8] Most of the team members and leaders are unionized. The union negotiates collective bargaining agreements, provides social and health services, and advocates for improved working conditions for the workers.[9] Different parts of the car are produced simultaneously by different sectors: chassis and car-body components are manufactured and connected by the Press and Welding sectors, while other parts are produced by the Frame & RX Axle, Engines, and Resin

[8] See Adhvaryu et al. (2023a) for more details.

[9] See Section A in Appendix for more institutional details.

sectors. These parts are then assembled together in the Assembly sector, which is one of the most delicate phases of production.[10] Our study focuses on the Assembly sector, particularly the Trim and Chassis sub-sectors, as this is where the majority of learning and skill development occurs.

Quick Service Restaurant Chain The quick service restaurant chain is the Colombian subsidiary of a large multinational company. The firm employs $2,500$ workers across 52 stores nationwide[11]. Each restaurant operates with two points of sale: the counter (in-store) and the drive-through. Orders are recorded and automatically displayed on a monitor in the kitchen. The kitchen production process is organized into five distinct stations: grill, fryer, assembly, soda fountain, and desserts.[12] Each employee is assigned to a specific station within this production line for a given shift. Orders are assembled and delivered either at the counter or at the drive-through pick-up window by the worker stationed at the respective point of sale. In addition to the kitchen operations, other support operations occur simultaneously, including cleaning of facilities, machine maintenance, and management of security and parking. The company's objective is to ensure timely service and high quality standards in service.

Retailer The retail company is the Colombian subsidiary of a Latin American firm, employing $25,400$ workers across 83 stores.[13] The firm operates a diverse range of store formats, from large locations comparable to supermarkets and hypermarkets in the United States to smaller stores with a footprint of roughly 2,000 square feet. Each store includes different departments: Customer Service, Product Replenishment and Display, Cashier and Payment, Logistics and Storage, Security, and Administrative Support. Each store needs to ensure that products are readily available, transactions are processed smoothly, and customers receive high-quality service.

2.2 Organizational Structure

Despite significant differences in terms of primary activities, the three firms share a similar three-layered organizational structure comprising of central headquarters (CHQ, where the main strategic direction, financial decisions, production processes, and HR policies are determined), middle management working in the plant/stores (who have a primary role of supervising production activities and managing/coaching workers), and front line workers (who are in charge of production activities).

[10] Notably, 75% of the defects per vehicle occur during this stage.

[11] The final sample includes 52 stores. We exclude those treated (i.e., partner with the last mile delivery company) before the start of the observation window, as well as those for which we lack manager mobility data.

[12] See Adhvaryu et al. (2023b) and Adhvaryu et al. (2022) for more details.

[13] The final sample includes 83 stores. We exclude those treated (i.e., partner with the last mile delivery company) before the start of the observation window, as well as those for which we lack manager mobility data.

All firms adopt centrally designed, standardized management practices in production, which are cascaded to units (teams in the case of the car manufacturer and stores for the retail company and quick service restaurant chain).[14] Production is organized across units of similar size, and tasks are standardized within each unit.

In each of the three firms, production takes place in working units led by middle managers, who are in charge of driving operational efficiency and performance in their teams. Middle managers oversee various activities, including personnel management, training, and workflow coordination, and are responsible for maintaining quality standards and addressing operational issues. They typically lead teams, support front-line workers, and assign workers to tasks to ensure they are completed following centralized guidelines. They are typically not in charge of hiring new workers, but they make recommendations for promotions and are consulted by HR before a promotion is made.[15]

2.3 Training and Managerial Rotations

The three firms included in this study are large, structured organizations, which make use of structured management practices to coordinate a wide range of activities. In particular, across all three firms, key HR practices (such as recruitment, hiring, compensation, incentives, and promotion criteria) are determined centrally at CHQs. This includes two policies that are critical to our study, training and managerial rotations.

The three firms considered in this study centralize the design of training policies in the HR function. These programs are tailored to specific occupations, positions, and tasks in the firm. Each company offers a diverse range of training initiatives, but broadly they can be seen as investments in firm-specific skills acquisition.[16] Training opportunities are widely communicated through central messaging to front-line employees, who are compensated for the time they spend in training. While there are no explicit bonuses tied to training completion, the three firms explicitly communicate that the acquisition and retention of new skills are necessary for lateral moves and promotions within the companies. This approach is meant to foster continuous learning and skill development,

[14] All three firms adopt most of the operational and HR management practices surveyed in Bloom and Van Reenen (2010).

[15] Middle managers' influence varies slightly across the three companies: promotion decisions are relatively more centralized in the car manufacturer than in the quick service restaurant chain and the retail company. In all three companies, managers are compensated with a mix of fixed and variable wages. The variable component of the wages depends on production: for the car company the variable component represents 10% of total compensation, in the quick service restaurant it is close to 30%, and in the retailer it varies between 30 and 50% depending on store formats. Variable compensation is not related to training. More details on the specific responsibilities of middle managers are provided in Section A.2 in Appendix.

[16] In each of the three firms, training is conducted by dedicated staff within the unit/store in which the team is located, except for the car manufacturer, which conducts some training modules in a dedicated training line. The specific content of the programs is described in Section A.3 in Appendix.

encouraging workers to progress in their careers and take on more complex and responsible roles over time.[17] Middle managers are not compensated for workers getting trained and they do not have active roles in any training-related activity except for the certification of skills acquisition after completion.[18] As we will discuss in more detail in the next section, however, middle managers often advice employees on career development, including training opportunities.

The second HR policy that is critical for our paper is that middle managers are rotated regularly across teams for developmental reasons, uncorrelated with the performance or training of their past or future teams.[19] In the car manufacturer, workers move to different working groups when opportunities arise to learn new tasks in the production process and following a promotion from team members to team/group leaders. Similarly, in the quick service restaurant chain and retail company, managers rotate across stores by headquarters to expose them to different store formats and environments for developmental reasons. These rotations allow us to study the effect of middle managers for training take-up in isolation from other team or workers' characteristics.

2.4 Demand Shocks

Each of the three companies experienced a positive demand shock, which led to a discontinuous increase in production during our sample period. For the car company, CHQ responded to the shock via two large increases in production targets, the first occurring four months into the panel data, and the second approximately nine months into the panel. The company aimed to achieve these new production goals primarily via a reduction in takt time—the required product assembly duration that is needed to match demand. The odds of success in doing so are directly related to workers' skills, since the adjustment requires task specialization (breaking down complex tasks into smaller, more focused activities) and flexibility (being able to seamlessly move across tasks along the production line as needed) on the production line. While the firm announced the planned production increases to managers and workers in advance, it did not immediately adjust wages or headcount in response or anticipation of the shock, since these adjustments require long negotiations with unions. The increases in production were implemented simultaneously across the plant for all working groups, so that we can examine only the before and after change in business and HR outcomes across units.

For the quick service restaurant and retail firms, the sudden increase in production was driven by the introduction of an app service that allowed consumers to order items and have them delivered to their preferred location. The app acted like a positive demand shock, since it significantly increased transactions and sales (that is, it was not merely a substitution of in-person customers with online

[17] These incentives are broadly similar to the contract for firm-specific skills acquisition studied in Prendergast (1993).

[18] This activity is not additionally compensated.

[19] The use of managerial rotations for developmental reason is frequent in large, structured organizations (see, for example, Minni (2024)). The lack of relation between managerial rotations and team training and/or performance was reported to us by the firms, and we also verify that this is the case in the empirical analysis.

customers). The sudden and large expansion of the customer base and transaction volume meant that workers now had to manage both in-store and delivery orders, interactions with delivery workers, and increased variation in orders between peak and non-peak hours. This, in turn, increased the value of having workers equipped with the skills and certifications needed to operate across different stations in the stores, especially those more related to the interaction with delivery orders, and possibly work in different tasks over the day.[20] Also in this case, the introduction of the delivery app was not matched by increases in wages or headcount, since in both firms wages are typically adjusted annually and hiring is centralized. The rollout of the delivery app program was staggered across stores. The order of the rollout did not correlate with training take-up or total productivity, but depended on factors such as local regulation and platform penetration in a particular region, among others. We thus use a staggered event study approach to estimate the impact of the shock.

While occurring in different settings and in somewhat different modalities, the sudden increases in production share some important aspects across the three firms. First, they were exogenous to the units, i.e. uncorrelated to the units' performance or training intensity. Additionally, they all increased the importance of firm-specific skills in production, in that they made it more valuable to have workers who could seamlessly work across different tasks in production. Third, they did not involve any meaningful wage increase for workers or managers, nor additional headcount. This allows us to isolate whether middle managers facilitated or hindered the adjustment to an organizational change, while holding wages and other formal HR policies constant.[21]

3 Data

3.1 Data Sources

Primary Data A unique feature of the study is the use of rich, comparable personnel and production data across three distinct organizations. We use the following data:

- *Performance data* (total production, productivity) at the weekly level. For the restaurant chain and the retail firm, the data is available at the store level, while for the car manufacturer, production data is at the plant level.

- *Personnel records*, which include basic demographics, date of hiring, promotions, demographics, absenteeism, and turnover at the employee level. The data also allow us to track workers and managers over time and identify their current position (and historical data on previous

[20] See Adhvaryu et al. (2023b) for more details.

[21] This approach is similar to the one used in Aghion et al. (2021), who study how greater decentralization—i.e., giving middle managers greater autonomy in decision making–helped firms cope with the Great Recession.

positions) and unit (team or store) within the company. Leveraging these data, we can build a comprehensive workers- and managers-store panel.

- *Training data*, including the records of specific training programs completed by all the workers and managers at the week level. A comprehensive qualitative description of the training programs for the three companies allows us to classify them into operational and non-operational training programs.

The data are longitudinal in nature for all three firms, though the exact length of the panel varies across organizations. For the car manufacturer, we have access to data between January 2017 and October 2019; for the quick service restaurant chain, the data reflect the time period between July 2018 and November 2019. Finally, for the retailer chain, the data cover the time period from January 2017 to March 2020. We aggregate the data across all firms at the team and biweekly level: 196 working groups for the car manufacturer, 52 stores for the quick service restaurant chain, and 83 stores for the retailer.

Auxiliary data For the quick service restaurant chain and retail company, we collected self-reported data on middle manager traits and management practices with a detailed online survey designed and implemented in partnership with the firms. The survey covers four main areas of managerial responsibilities: decision-making approaches, psychometric measures including the Big Five personality traits (openness, conscientiousness, extroversion, agreeableness, and emotional stability), leadership style (e.g., managing interpersonal conflicts, time management), and planning, management, and organizational practices. The survey for the quick service restaurant chain was conducted in March 2023, achieving a 90% response rate, with 378 managers participating. For the retail company, the survey was conducted in September 2022, collecting information from 380 managers, with a response rate of approximately 70%.[22]

We also complement our data with measures of labor market characteristics and total rainfall as a proxy for increased cost of effort of the workers to attend their work (we use these data in Section I). We use data from the Colombia National Administrative Department of Statistics (DANE) for the labor market. This dataset provides monthly occupation and employment data for 24 departments, including unemployment, informality, and household employment rates. We use weather data from the Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM) in Colombia for

[22]The higher response rate for the quick service restaurant chain was influenced by the fact that each manager received an email from the head of the company in Colombia, asking them to complete the survey. The company followed up with each manager who had not completed the survey every week for two months. For the retail compan, we selected a random sample comprising 35% of the managers across the four brands owned by the retail company. We use data for the largest brand of the retail company. The managers received an email with instructions on how to complete the survey. As in the case of the restaurant chain, the company tracked those who did not complete the survey for two months.

the total rainfall. This dataset includes daily measurements of rainfall and temperature from 303 stations. We assign weather variables to municipalities where the quick service restaurant chain and retail company have a presence, using inverse-distance weighting.

3.2 Summary Statistics

Table 1 presents the summary statistics for the main performance, training and HR variables used in the analysis.[23]

3.2.1 Averages

Car Manufacturer On average, the plant produces around 105,000 cars each year. Each working group consists of around 14 members. Each worker has an average tenure of around 7.75 years, and each year, 44% of employees are absent at least once. On average in a biweekly period, around 1 employee is absent (this equates to around 7 percent of the total workforce).

Each year, around 1.62 employees leave the working group, around 5.48 are hired, and around 7.55 receive a promotion. Training programs require several hours and, is some cases, they occur in a dedicated training line. Annually, about 22 training programs are initiated within a unit, and 17% of the workforce participates, with an average of 2.9 programs per employee. Just less than half of these programs are on the job and technical in nature.

Quick Service Restaurant Chain We use scanner-level data to measure store sales, the number of units sold, and the total number of transactions at the store level. Throughout the paper, we use the number of transactions (the number of total orders fulfilled by the store) as a measure of store production during a given period. On average, each store sells around $1,084,000$ USD a year, around 679,000 units, and around 263,000 transactions.

A store generally has around 22 workers at any given time. These workers have, on average, 1.3 years of experience in the store. In each biweekly period, around 3 workers are absent, which is close to 13% of the workers. Each year, 11 employees leave the store, 15 are hired, and 6 are promoted.

Training programs in the quick service restaurant chain are all on the job and are designed to teach employees to manage stations and prepare them for the general store operation. Each year, in a particular store, about 327 training programs are started on average, and 80% of the workforce is trained, averaging 13 training programs per employee.

[23] The primary performance measure for the car company is the total number of cars produced which is only available at the plant level. For the quick service restaurant and retail companies we use total sales at the store level.

Retailer We use scanner-level data from store sales to calculate total sales, the number of units sold, and the total number of transactions at the store level. On average, around 20.6 million USD are sold annually at each store. Each store typically employs 113 workers at any point in time. These workers have an average tenure of 4.27 years. Each biweek, close to 6.5 workers are absent, which equates to 5.1 percent of the total workforce. Each year, 44.33 employees leave the store, 47.42 are hired, and 14.36 receive a promotion.

Training programs involve both on-the-job training to manage stations and training related to overall store operations. In a given year, 138.41 training programs are started on average in a store, with 26% of employees engaging in at least one training program. For operational and technical skills training programs, each store takes up 14.45 training sessions annually, with 7% of employees trained, averaging 1.13 training programs per employee.

3.2.2 Within Firm Variation in Performance, Training and other HR outcomes

In each of the three firms we see considerable within-firm variation in both performance and key HR metrics, such as absenteeism, turnover, hires, and promotions, as shown by the large standard deviations in Table 1. For example, while the average share of employees ever absent during a two-week window is 7% for the car manufacturer, 13% for the quick service restaurant chain, and 5.2% for the retailer, the standard deviation across units is 5% for the car manufacturer and the quick service restaurant chain and 3% for the retailer. These differences become even more pronounced when considering the average share of employees ever absent during a year: the mean (standard deviation) for the three firms is 44% (34%) for the car manufacturer, 58% (15%) for the quick service restaurant chain, and 45% (46%) for the retailer.

We also see sizable variation within each of the three firms in other key HR metrics such as turnover, hiring, and promotions, and training take-up. For example, the mean (standard deviation) of the share of trained employees in the team is 17% (16%) in the car company, 80% (16%) for the quick service restaurant chain, and 26% (9%) for the retailer. We see similar variation on the intensive margin when we consider average training programs started per employee (conditional on starting at least one training program).

The considerable within-firm variation in key metrics and training take-up suggests that, despite being centralized in their design, the same HR policies result in different outcomes within the same firm. In the next section, we will study the extent to which this within-firm variation may be explained by differences across middle managers, as opposed to worker or unit-level characteristics.

Table 1: **Summary Statistics of Performance, HR Measures, and Training Across Firms**

	Car manufacturer		Quick Service Restaurant Chain		Retail Company	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Performance Measures (Unit level, annual cumulative)						
Cars produced (plant level)	105,000	-				
Sales ('000 of US dollars)			1,084.11	453.84	20,595	16,727
Units sold (Num. of units sold)			678,639	291,188	4'417,662	3'488,097
Number of Transactions (Num. of completed orders)			263,424	116,064	3'019,110	2'273,481
Sales per Employee ('000 of US dollars)			50.812	13.142	215.513	77.552
HR Measures (Unit level)						
Workers per unit (Num. of employees)	14.66	8.21	22.27	9.94	112.94	101.55
Employee tenure (Years)	7.75	5.38	1.35	1.23	4.27	6.98
Number of absent employees (Num. of absent employees each biweek)	1.03	0.77	3.01	2.13	6.49	7.31
Share absent employees (Share each biweek)	0.07	0.05	0.13	0.05	0.051	0.03
Share employees ever absent in the year (Share ever absent in the year)	0.44	0.34	0.58	0.15	0.45	0.46
Turnover (Num. of employees exiting each year)	1.62	3.78	11.49	7.09	44.33	59.72
Hired (Num. of employees hired each year)	5.48	8.30	15.28	10.15	47.42	68.17
Promotion (Num. of employees received a promotion each year)	7.55	9.13	6.10	2.92	14.36	12.05
All training (Unit level, annual cumulative)						
Average n. of training programs started	22.08	29.50	327.08	149.78	138.41	129.02
Share of trained employees	0.17	0.16	0.80	0.16	0.26	0.09
Training programs per employee	2.90	1.28	12.7	2.82	2.57	0.56
On the job training (Unit level, annual cumulative)						
Average n. of training programs started	9.80	16.55			14.45	14.30
Share of trained employees	0.11	0.13			0.070	0.040
Training programs per employee	1.76	0.70			1.13	0.15
Content	Developing technical and specialized production skills (safety, quality, and technical training)		Managing food stations inside the store		Managing store operations	

Notes: Table 1 reports the annual summary statistics for each company. For the car company, the main performance measure is the number of cars produced at the plant level in a given year. For the retail company and quick-service restaurant chain, performance measures are computed at the store level. All HR, training, and on-the-job training measures are calculated at the unit level for the three companies.

For the HR measures of all firms, we present two types of measures: annual cumulative measures, which add the indicators for each biweekly period every year, and biweekly measures, which simply calculate the statistics at the biweekly level. Summary statistics for *Workers per unit*, *Employee tenure in years*, *Number of absent employees*, and *Share of absent employees* are calculated at the biweekly level. The interpretation is as follows: for example, every biweekly period, there are 14.66 workers in each unit on average. *Turnover*, *Hired*, *Promotions*, and *the Share of absent employees in the year* are calculated as annual cumulative. This can be interpreted as 1.62 employees exiting the unit in a year on average.

Both all training measures and on-the-job training measures are calculated as annual cumulative at the unit level. For example, 17% of employees in a unit, on average, received at least one training session in a given year.

For the car company, the sample consists of store-biweekly panel data for 196 working groups between January 2017 and October 2019 across 196. For the quick service restaurant chain, the sample consists of store-biweekly panel data for 52 stores from June 2018 to November 2019. Finally, for the retail company, the sample consists of store-biweekly panel data for 83 stores from January 2017 to March 2020.

4 Estimating the Role of Middle Managers for Training

As discussed in Section 2.3, the firms in our sample centralize the design and communication of training programs that are conducted inside the firm. Our interactions with the companies, however, suggest that there is variation in the support for training and employee growth across middle managers within the same firm. For instance, during our structured on-site interviews,[24] some middle managers told us that they actively communicated training opportunities to their employees, viewing them as essential for career advancement. These same managers tended to see the lateral or upward mobility of their workers as a positive outcome and a personal achievement and took pride in their role as advocates for talent development within the firm. However, other middle managers were less involved or regarded training as a potentially wasteful activity, distracting workers from their job. Conceptually, these different attitudes are akin to the variation in "people skills" across middle managers documented in different sectors in Hoffman and Tadelis (2021) and Minni (2024). The empirical question that we tackle in the next sections is whether middle managers matter for training take up among employees and the extent to which their role for training take-up is related to their different approaches towards workers' development.

4.1 Identifying Managerial Fixed Effects in Training

We estimate the value added by managers in training take up across units within the same firm (teams for the car manufacturer and stores for the quick service restaurant chain and retailer) by leveraging the routine rotation of managers (workers in the case of the car company) across units. As discussed in Section 2.3, crucially, these rotations happen for reasons unrelated to performance and/or training take-up and can, therefore, be considered to be exogenous to these outcomes.

Following Abowd et al. (1999) we use an AKM model with training take up as the outcome variable to estimate the value added by managers, controlling for time and unit fixed effects. For the quick service restaurant and retail company, we estimate manager and store fixed effects, while for the car company, we estimate worker and manager fixed effects. We estimate the following two-way fixed effects model:

$$TR_{ijt} = \theta_i + \psi_{J(i,t)} + \delta_t + \varepsilon_{ijt}, \tag{1}$$

where the dependent variable, TR_{ijt}, is the total number of training programs taken in unit j reporting to manager i, in bi-weekly period t.[25] In the case of the car manufacturer, $\psi_{j(i,t)}$, refers to

[24] We talked to 10 group leaders of the assembly line in the car company, 12 managers of different stores of the quick service restaurant, and visited eight stores and spoke with multiple shift and general managers of the retail company.

[25] Training is counted regardless of completion status.

a worker-fixed effect, and in the case of the quick service restaurant chain and retail company, it refers to a store-fixed effect. θ_i is a fixed effect for the manager. δ_t is a date (bi-weekly) fixed effect that accounts for the seasonality of the production or sales as well as the general changes that the firm implements based on periodic goals.

We follow Card et al. (2013) and decompose the error term in (1), ε_{ijt}, into a match-specific component, $\eta_{J(i,t)}$; a unit root component, ξ_{it}; and a transitory error, ν_{ijt},

$$\varepsilon_{ijt} = \eta_{J(i,t)} + \xi_{it} + \nu_{ijt}. \tag{2}$$

The identification of manager and unit fixed effects relies on the assumption that the assignment of managers to workers is conditionally mean-independent of past, present, and future values of ε_{ijt}. This assumption allows managers to be assigned to units based on the permanent components of managerial ability (θ_i) and unit components (ψ_J), permitting sorting on these fixed effects. However, it excludes the possibility of managers being assigned to units based on their match-specific component ($\eta_{J(i,t)}$) or transitory shocks to store training performance (ν_{ijt}). If managers were to sort based on these factors, it would result in biased and inconsistent estimates of the fixed effects due to endogenous mobility.

Likewise, as discussed in Abowd et al. (2002, 1999), the manager and unit fixed effects in this model are separately identified only within "connected sets" of units (teams or stores), linked by managers moving across units (in the case of the quick service restaurant and retail company) or by workers moving across teams (in the case of the car company). We identify 1 large connected set (CS) for the car company, 7 CSs for the quick service restaurant chain, and 14 CSs for the retail company. We estimate Equation (1) within each connected set.[26]

Figure 1 shows the distribution of manager training fixed effects separately in each firm. We standardize the fixed effects by the mean of the connected set and present the kernel density on a scale from zero to 100.[27,28] The y-axis presents the density, while the x-axis presents the standardized fixed effects for all the connected sets in each company. For the car manufacturer, a manager ranked at the 10th percentile of the fixed effects distribution is associated with 1 training program per working group every two weeks. In contrast, a manager at the 90th percentile shows 6 training programs being taken up by workers per working group every two weeks. The numbers are similar for the retail company: a manager in the 10th percentile is associated with 2.18 training programs per store every two weeks, while a manager in the 90th percentile has 3.78 training

[26]Later in the paper, we analyze the AKM model's limitations and implement several robustness checks and alternative specifications.

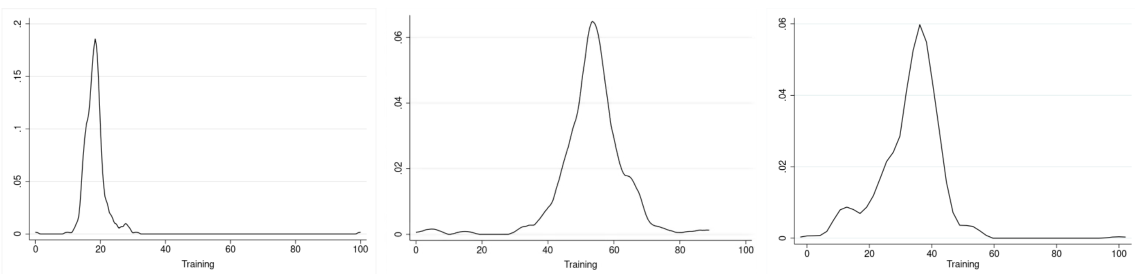
[27]Specifically, we subtract the minimum value and divide by the range (maximum minus minimum), then multiply the result by 100 to scale the fixed effects between 0 and 100.

[28]Later in the paper, for comparison purposes, we compare manager fixed effects for training and sales. To do this, we estimate the fixed effects of the units and managers for the quick service restaurant and retail companies using log(sales/employees) as the dependent variable.

programs per store every two weeks. The distribution of fixed effects in the quick service restaurant chain shows even larger differences: 2.1 training programs per store every two weeks for managers at the 10th percentile, and 21.55 training programs per store every two weeks for a manager in the 90th percentile.

Figure 2 illustrates the share of the training variance across units that can be attributed to managers and unit fixed effects.[29] In all three cases, middle managers account for a large fraction of the variance in training take up across stores/units, ranging between 20% for the retailer, 25% for the car manufacturer, and 55% for the quick service restaurant chain. In all the three companies, the contribution of manager fixed effects to the training variance is higher than that of the unit fixed effects.

Figure 1: **Distribution of Manager Fixed Effects in Training Take-Up Across Firms**



(a) Car Manufacturer

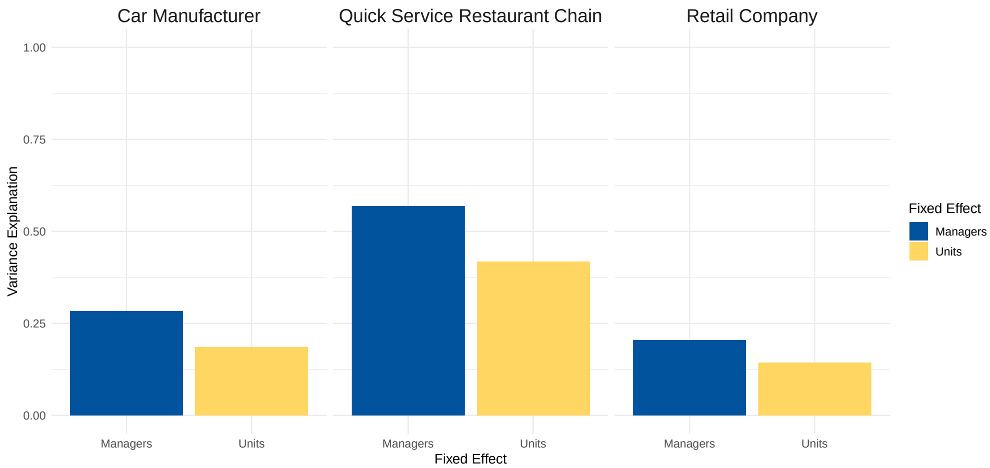
(b) Quick Service Restaurant Chain

(c) Retail Company

Notes: Figure 1 shows the distribution of manager fixed effects obtained from estimating equation 1 using training take-up as the outcome variable. The values are standardized between 0 and 100, subtracting the minimum value and dividing by the range (maximum minus minimum), then multiplying the result by 100. For the car company, the sample consists of store-biweekly panel data for 196 working groups between January 2017 and October 2019 across 196. For the quick service restaurant chain, the sample consists of store-biweekly panel data for 52 stores from June 2018 to November 2019. Finally, for the retail company, the sample consists of store-biweekly panel data for 83 stores from January 2017 to March 2020.

[29] We compute the ratio of the training variance to the variance of the manager/unit fixed effects for each connected set within each company.

Figure 2: **Variance decomposition Manager vs. Unit Fixed Effects**



Notes: Figure 2 shows the proportion of total variance in the training variable across stores (quick service restaurant and retail companies) and working groups (car company) that is accounted for by manager and unit fixed effects, respectively. We compute the ratio of the variance attributable to the manager (blue) and unit (yellow) fixed effects relative to the total variance. A value of 1 indicates that the variance of fixed effect of the manager or unit fully accounts for the training variance, while a value of 0 indicates that no portion of the total variance can be attributed to the variance of the fixed effects. For the car company, the sample consists of store-biweekly panel data for 196 working groups between January 2017 to October 2019. For the quick service restaurant chain, the sample consists of store-biweekly panel data for 52 stores from June 2018 to November 2019. Finally, for the retail company, the sample consists of store-biweekly panel data for 83 stores from January 2017 to March 2020.

4.1.1 Identification Assumptions

To consistently estimate the parameters in Equation (1) by OLS in the AKM model, we make the following identification assumptions following Card et al. (2013):

$$\mathbb{E}[\theta_i \varepsilon_{ijt}] = 0; \tag{3}$$

$$\mathbb{E}[\psi_{J(i,t)} \varepsilon_{ijt}] = 0; \tag{4}$$

The error term is independent of store/working group fixed effects (3) and worker/manager fixed effects (4) . Section B in Appendix discusses the checks we performed to establish the validity of the identification assumptions underlying the AKM model, which we summarize below.

Sorting on Training or Productivity Identifying the unit/manager fixed effect requires a strong exogeneity assumption, i.e., that the assignment of managers to units (or workers in the case of the car company) must be conditionally mean-independent of the past, present, and future values of the error term (Adhvaryu et al., 2020; Card et al., 2013). This implies the absence of any sorting of units/managers and managers/workers based on the match-specific component of the dependent variable, such as total training, or other transitory shocks to training. Any sorting based on the total error term would result in inconsistent estimates of the fixed effects. However, the assumption does allow for sorting based on the fixed effect term or positive assortative matching of workers/managers and managers/units (Card et al., 2013). To establish the validity of this identification assumptions, we check for endogenous mobility of managers/workers on the match-specific component of training or by training shocks. We follow Card et al. (2013) and Adhvaryu et al. (2020) and perform a series of tests for endogenous mobility based on training or productivity and find no evidence of sorting based on training take-up or productivity.

Pretrends A second concern about the independence of the error term ξ_{kt} arises if managers or workers who are on a particularly positive training trend—those who appear to increase training before the move—at a given unit or store are more likely to move to stores or units with higher training, while those on a negative training trend—those training fewer workers before the move—are more likely to move to stores or units with lower training. This would lead to an overestimation of the store or unit effect for high-training stores and an underestimation for low-training stores. We find no clear direction in the trends prior to moves for high and low-training managers.

Limited Mobility Bias Finally, the identification of both manager and unit fixed effects in the AKM model requires observing a sufficient number of managers over time in different units, ensuring adequate mobility. Limited mobility bias may lead to biased estimates of the correlation between manager and unit effects (Abowd et al., 2004; Andrews et al., 2008, 2012). We find evidence of substantial mobility in each of the firms, comparable to prior studies and even larger than in typically matched employer-employee data. Nevertheless, we perform the bias correction procedure suggested by Andrews et al. (2008) as suggested in the literature. The main results are largely robust across all correction methods implemented.

4.2 Portability Analysis

To better illustrate the impact of managers on employees' training, we study how training take up changes after the arrival of a High-Training (henceforth HT) manager in a unit previously managed by a Low-Training (henceforth LT) training manager. We categorize managers as HT if their value added to total training take-up is above the median of the fixed effect distribution for each firm (adjusted for median correction at the connected set level). The remaining managers are classified as LT.

An event is defined as the arrival of an HT manager to a unit previously managed by an LT manager. These events are staggered within firms across different units. In 68% of the total observations (store-biweek pairs) for the retail company and 60% for the quick service restaurant chain, we observe more than one manager per store. This reflects, as mentioned before, the presence of different middle managers within a store for both the retail company and the quick service restaurant chain. When there is more than one manager, we define an event as occurring when there is a change in manager, and the status of the store changes from being managed by an LT to being managed by an HT manager.[30]

We estimate the following equation:

$$TR_{jt} = \sum_{-2\leq k\leq 2, k\neq -1} D_{jt}^{k}\beta_k + \phi_j + \theta_t + \varepsilon_{jt}, \tag{5}$$

where TR_{jt} is total training modules taken up by unit j in period t (pooled across 8 weeks); ϕ_j and θ_t are unit and time FEs, respectively; τ_j is the first period when unit j is assigned to HT manager; $D_{jt}^{k} = 1[t = \tau_j + k]$ for $k \in (-2, 2)$ is the relative time-to-treatment dummy. Finally, the standard errors are clustered at the unit level

We find that the arrival of an HT manager to a unit previously under an LT manager significantly boosts training take-up (see Figure 3). For the car manufacturer and the retailer, the arrival of an HT manager increases training take-up both in the immediate eight weeks after the arrival and eight weeks or more after the arrival. For the car company, the arrival of an HT manager increases training take-up by about 6.82% in the first weeks after the arrival and about 8.38% after eight weeks on average. In the retail company, the increase is 59% and 39% respectively. Meanwhile, in the quick service restaurant chain, the arrival of the HT manager increases training take-up by 55% in the first few weeks after the arrival, though the effect seems to fade eight weeks or more after the arrival. For all three companies, we observe no pretends in training take-up prior to the arrival of an HT manager.[31]

4.3 Training Specialization and Team Composition

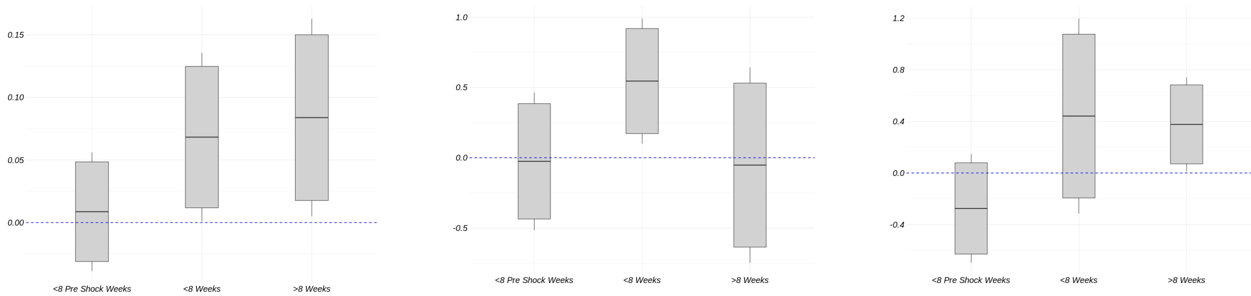
We study whether differences in HT status merely reflect specialization in shorter training modules, different team composition (specifically, a higher share of less experienced workers, who would mechanically need more training to be onboarded), or higher probability of being assigned to less intense shifts (when the opportunity cost of training may be lower).

[30] We also control if there is an overlap in the pre-or post-treatment period with the arrival of a manager to the same store.

[31] To check the robustness of this result, we repeat the same exercise but we divide the complete panel into two sub-samples: in the first sub-sample, we estimate the AKM in the period prior to the arrival of the manager to identify the manager's fixed effects (that is, excluding the contribution of the unit where the manager arrives to the estimation of the fixed effects), and use this sample to classify them as High-training (HT) and Low-training (LT). In the second sub-sample, we estimate the impact of an HT manager's arrival on a unit previously managed by an LT manager. The results are largely robust to this alternative method, as shown in Figure C.1 in the Appendix. Unfortunately, due to how teams are constructed, we can not estimate this regression for the car company.

Figure 3: **Arrival of a High Training Manager and Workers' Training Take up**

(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company



Notes: Figure 3 reports the results for the estimation of Equation 5. We plot the percentage change in training take-up after the arrival of an HT manager in a working group (panel a) or store (panels b and c) that were previously assigned to an LT manager, in the first eight weeks and after eight weeks upon the HT manager's arrival. For the car company, the effect in the first eight weeks is 6.82%**, and after eight weeks is 8.38%**. For the quick service restaurant chain, the effect in the first eight weeks is 54.53%**, and after eight weeks is -4.16%. For the retail company, the effect in the first eight weeks is 44.11%, and after eight weeks is 37.66%**. Standard errors are clustered at the unit level. The bars in the graph represent the 90% confidence intervals, while the lines indicate the 95% confidence intervals. *** p<0.01, ** p<0.05, * p<0.1.

Training specialization HT managers may be merely focusing on shorter or simpler programs. To explore this possibility, we divide training programs taken up by teams into distinct sub-types. For the car manufacturer, training programs include leadership and team skills, safety protocols, line management, and quality control training. In the quick service restaurant firm, the training programs encompass kitchen operations, customer experience enhancement, lobby service, and preparation of hot and cold drinks. The retail firm provides training in on-the-job skills, virtual training sessions, and face-to-face instructional programs. We plot the rate of training by HT managers compared to LT managers for each type of training. A ratio of one indicates that HT managers train exactly as many employees in a training type as LT managers do. Figure 4 shows that there is no strong evidence of training specialization. HT managers seem to train their supervised workers in all operational training types, regardless of the specific sub-type.

Team composition Another possible concern is that the HT manager status may merely reflect systematic differences in team composition related to training. For example, HT managers may be assigned to teams with more unexperienced workers, who are more likely to require onboarding training programs. However, Table D.2 in Appendix shows that, if anything, HT managers tend to work with employees with more experience (this is the case in the car manufacturer and the restaurant chain).[32]

[32] On average, highly-trained employees tend to have longer tenure and to be older. See Appendix Table D.1 for details.

Figure 4: **High Training Managers and Training Specialization**

(a) Car Manufacturer

(b) Quick Service Restaurant Chain

(c) Retail Company

Notes: Figure 4 illustrates the ratio of trained employees managed by HT managers to those managed by LT managers, categorized by training type across the three companies. For the car manufacturer, we examine group leadership, team skills, and Kaizen, safety, line management, and quality control. The quick service restaurant chain focuses on training categories, including kitchen, customer experience, lobby service, and hot and cold drinks preparation. For the retail company, the analysis includes on-the-job training, virtual training, job performance and technical skills, and face-to-face training.

Shifts Similarly, HT managers could be more likely to be assigned to "easier" or less intense shifts, where the opportunity cost of time spent training is lower. We can test this hypothesis only for the quick service restaurant chain, where we can observe shift assignments. We find no evidence of differences in shifts between HT and LT managers (Figure D.1).

Overall, the analysis suggests that the distinction between HT managers and others captures meaningful differences in training intensity that are not mechanically driven by a specialization in easier training modules, systematic differences in team composition or assignment to calmer shifts.

4.4 Characteristics, Practices and HR Outcomes of High Training Managers

In this section, we provide more evidence on the individual characteristics, attitudes and practices of HT managers.

Demographic Characteristics Who is an HT manager? To investigate this point, we start by exploring whether the median values for age, tenure, and gender differ significantly between HT and LT managers. Our analysis reveals no significant differences between HT and LT managers in any of the demographics. Table 2 summarizes these results for age, and gender, for the quick service restaurant chain and the retail company, though we see some difference in tenure for the retailer (HT managers are younger).[33] Thus, there is no evident manager demographic "profile" that is associated with being an HT manager.

[33] We do not have access to demographic data for the car manufacturer.

Table 2: **Differences in Demographic Characteristics between HT and LT Managers**

	Quick Service Restaurant Chain (N=360)			Retailer (N=277)		
	LT	HT	p-value (Difference)	LT	HT	p-value (Difference)
Age (years)	32.01	31.22	0.146	39.98	40.13	0.893
Tenure (days)	651.97	601.55	0.386	783.15	662.41	0.029
Gender (=1 if Male)	0.603	0.661	0.254	0.631	0.706	0.188
Education	6.634	6.813	0.303	7.974	8.1	0.694

Notes: Table 2 presents the differences between HT and LT managers across various demographic variables, including age, tenure, gender, and education, for both quick service restaurant chain and retail companies. The first two columns show the means of each variable for HT and LT managers, respectively, within each company. The third column displays the p-value from the t-test analysis of the difference in means between HT and LT managers. The education variable comes from the survey answers, where the managers selected their level of education from the following scale: 1- Elementary School incomplete, 2- Elementary School complete, 3- High School incomplete, 4- High School complete, 5- Technical Education incomplete, 6- Technical Education complete, 7- College incomplete, 8- College complete, 9- Graduate Studies incomplete, and 10- Graduate Studies complete.

Leadership Style and Management Practices We now explore whether HT managers differ in terms of their managerial and leadership approaches.[34] To do so, we leverage a large-scale management survey that was conducted in the quick service restaurant chain and the retailer, and correlate the survey responses with the estimated training fixed effects. We have complete survey responses for 360 and 277 managers for the restaurant chain and the retailer, respectively, but a smaller number could be matched with the estimated fixed effects (204 and 112, respectively).

We categorize the survey questions into four main areas: leadership traits, team outcomes and activities, adoption of structured management practices related to operations, and adoption of structured management practices related to human resources.[35]

- The *Leadership Traits* variables include conscientiousness, extroversion, agreeableness, openness, locus of control, self-esteem, Raven's Progressive Matrices (a non-verbal intelligence test), reading the mind rate, arithmetic skills, and digital span recall. These variables measure how HT managers perceive themselves and their capabilities, as well as their cognitive and emotional intelligence.

- The *Team Outcomes and Activities* category measures the self-reported total productivity problems faced by the manager, the number of active operations they oversee, and their daily operational activities.[36] These measures capture the perceived practical challenges and

[34] A substantial body of literature documents the importance of management practices and individual managerial traits in organizations for firm and team performance (Adhvaryu et al., 2021, 2022; Bloom et al., 2014, 2012; Bloom and Van Reenen, 2010; Frederiksen et al., 2020; Friebel et al., 2023; Hoffman and Tadelis, 2021; Metcalfe et al., 2023).

[35] The variables are created as indices derived from the questions in each section. A detailed description of each variable can be found in Section E in Appendix. The index values range from 0 to 100, with higher values indicating that the manager has a more positive self-assessment in the area of analysis.

[36] *Productivity Problems* reflects managers' reported issues over the past three months, such as equipment

workload that managers handle.

- The *Operations Practices* category measures the adoption of structured management practices aimed at supporting problem-solving and continuous improvement within the team. It includes measures of whether managers engage in problem-solving, the extent to which they put effort in identifying solutions to problems, whether they involve superiors and employees in problem-solving, the number of KPIs they set for the teams, the frequency of KPI reviews, the frequency of retrospective learning, Kaizen practices, and targets (short- and medium term goals).[37]

- Finally, the *Human Resources Practices* category covers different personnel management practices, including whether managers actively plan team composition, whether they value employee friendliness as a skill, whether they promote employees based on performance, whether they put effort in retaining star performers or talking to underperforming workers, whether they provide feedback to employees, and assess employees' well-being and motivation frequently. These measures capture HT managers' emphasis on employee well-being and motivation, their approach to performance management, and their interactions with both high and low performers.

To analyze the relationship between manager-fixed effects and the survey measures, we regress each individual manager-fixed effect on each survey variable. The coefficients for each survey category are then plotted in the corresponding Figures 5 and 6.[38] This shows that HT managers are distinct from others in some key dimensions. The left panel of Figure 5 shows that HT managers tend to be more extroverted, have better social skills, and are more likely to report higher levels of self-esteem and locus of control. Their levels of education, conscientiousness, arithmetic skills, and Raven test scores are, however, similar to those of LT managers. Likewise, the right panel of Figure 5 reveals that HT managers report fewer productivity problems but do not necessarily differ in the number of activities they engage in, which we consider to be a proxy for overall effort.

HT managers do differ from LT managers in terms of the adoption of participatory operations and personnel practices. The left panel of Figure 6 shows that HT managers review company objectives or KPIs more frequently, practice retrospective learning more often, and score higher

malfunctions, inventory shortages, absenteeism, and unmotivated workers. *Active Operations* measures how frequently managers engage in tasks like assigning duties, maintaining equipment, supervising cleanliness, conducting quality checks, and tracking sales changes. *Daily Operations* captures routine management activities, including store design adjustments, display arrangements, customer service, money handling, shoplifting prevention, premises maintenance, staff management, recruitment, and inventory optimization. Each index is constructed as an average of managers' responses.

[37] Kaizen refers to the continuous improvement of processes, emphasizing how often managers receive and implement suggestions regarding operations.

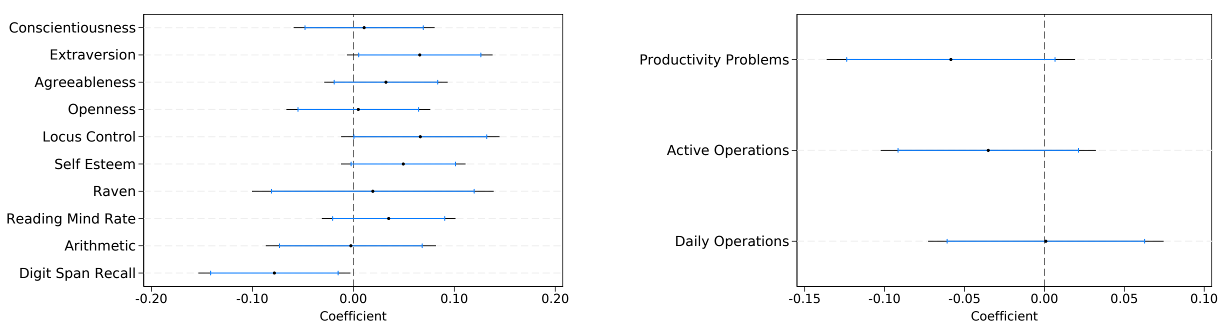
[38] Figures E.1 and E.2 present the robustness of these results after correcting for multiple hypothesis testing.

on questions measuring whether the manager received and implemented suggestions regarding operations from its team. The right panel of Figure 6 reveals that HT managers put a greater emphasis on employee well-being: they inquire about employee well-being and motivation more frequently, discuss KPIs with their employees more often, and engage more frequently with underperforming workers, while they are significantly less likely to focus their attention on top performers.

HR outcomes The survey findings suggest that differences in training outcomes across middle managers correlate with variations in managerial approaches and attitudes that place greater emphasis on teams and workers. Consistently with this hypothesis, Table 3 shows a strong and positive correlation between managerial training fixed effects and similarly estimated fixed effects in key HR outcomes, such as promotion, absenteeism and turnover rates.[39] Based on this evidence, we conclude that training fixed effects capture real differences in managerial attitudes, which are reflected in different team dynamics and outcomes.

Figure 5: **Self-Reported Leadership Traits and Activities and Managers' Fixed Effects**

(a) Individual Characteristics (b) Outcomes and Activities

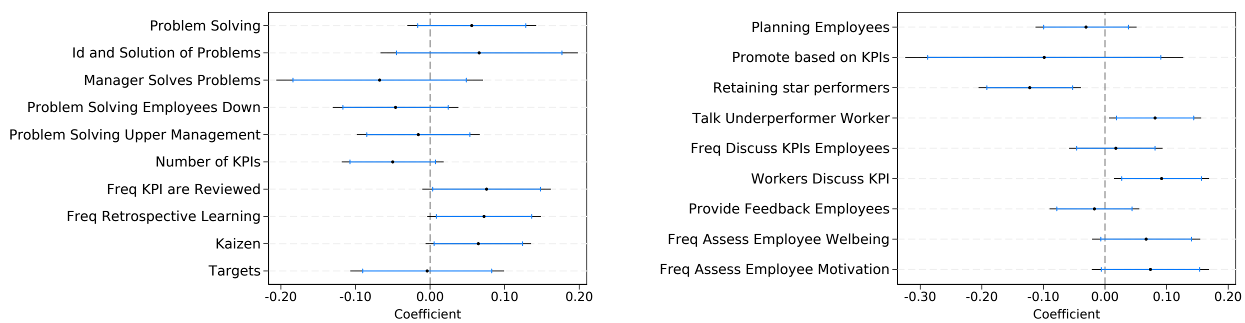


Notes: Figure 5 plots the coefficients from regressing the manager fixed effects on each survey variable score for each manager. The figure presents the coefficients from the main regression for individual characteristics as well as outcomes and activities for 204 managers from the quick service restaurant chain and 112 managers from the retail company. The black lines represent 95% confidence interval, and the blue lines the 90% confidence interval.

[39]We build the managers' fixed effects in these additional outcomes using the same approach used to build training fixed effects. See Appendix D for details.

Figure 6: **Self-Reported Adoption of Operational and HR Structured Management Practices and Managers' Fixed Effects**

(a) Operations (b) HR



Notes: Figure 6 plots the coefficients from regressing the manager fixed effects on each survey variable score for each manager. The figure presents the coefficients from the main regression for Operations and Personnel practices for 204 managers from the quick service restaurant chain and 112 managers from the retail company. The black lines represent 95% confidence interval, and the blue lines the 90% confidence interval.

Table 3: **Pairwise Correlations of Manager Fixed Effects Calculated for Training, Absenteeism, Turnover, and Promotions**

FE by	Absenteeism	Turnover	Promotion	Training
	Car Company			
Absenteeism	1			
Turnover	-0.025	1		
Promotion	-0.204***	-0.120*	1	
Training	-0.252***	-0.141**	0.285***	1
	Quick Service Restaurant Chain			
Absenteeism	1			
Turnover	0.001	1		
Promotion	-0.241***	-0.123***	1	
Training	-0.183***	-0.231***	0.181***	1
	Retail Company			
Absenteeism	1			
Turnover	-0.280	1		
Promotion	-0.234***	-0.022	1	
Training	-0.299***	-0.115***	0.365***	1

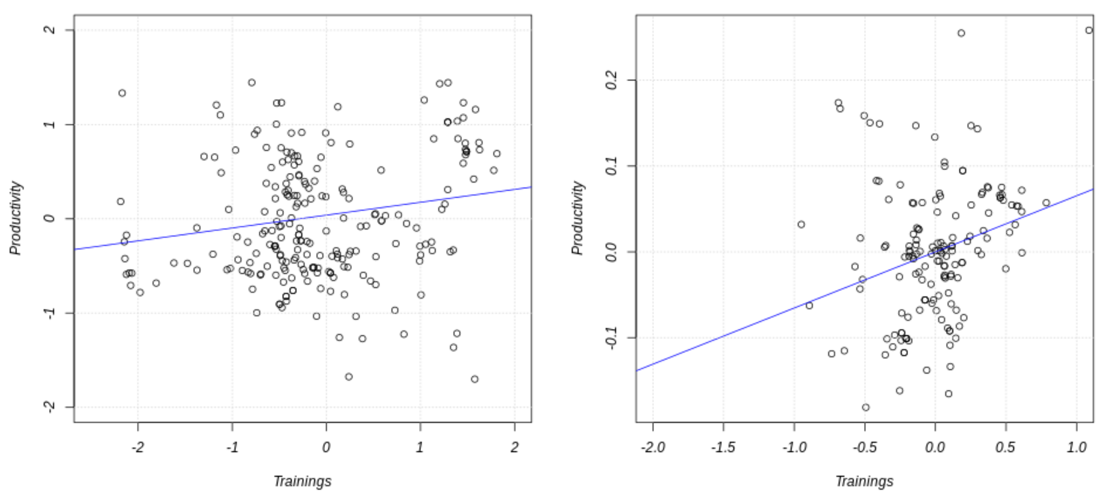
Notes: Table 3 reports the pairwise correlation of manager fixed effects estimated (dependent variable of Equation 1) for: Absenteeism (absent employees), Turnover (retired employees), Promotions (promoted employees), and Training (total number of trainings completed by all employees). The sample size for the correlation analysis for the Car Company is 309, for the Quick Service Restaurant Chain is 399, and for the Retail Company is 416. *** p<0.01, ** p<0.05, * p<0.1.

5 High Training Managers and Performance

Do differences in managerial value added in training matter for business performance? Intuitively, given the nature of and rationale behind the training programs examined in the previous section, we expect units led by HT managers to be, on average, more productive, with magnitudes that reflect the importance of tasks requiring firm-specific skills in production. Indeed, when we examine the correlation between managerial training fixed effects and productivity fixed effects, as shown in Figure 7, the correlation between the fixed effects is positive and significant: 0.121 for the quick service restaurant chain (significant at the 0.068 level), and 0.3 for the retail company (significant at the 0.001 level).[40]

Figure 7: **Correlation between Training and Productivity Managers' Fixed Effects**

(a) Quick Service Restaurant Chain (b) Retail Company



Notes: Figure 7 shows the correlation between training fixed effects and log productivity fixed effects for the quick service restaurant chain and retail company, using data (on average six months) before the demand shock. In the quick service restaurant chain, the correlation is 0.121, with a *p-value* of 0.068. For the retail company, the correlation is 0.27, with a *p-value* of 0.001.

Given their influence on training, however, HT managers may also facilitate their units' *adjustment* to new production needs, especially if doing so leverages skilled workers and/or requires workers to acquire new skills.[41] To study this idea empirically, we examine the three firms before and after a large and sudden increase in production—driven by a demand shock exogenous to the units, as discussed in Section 2—that prompted a change in the organization of work, and a relative increase in the value of firm specific skills in production.

In what follows, we explore the adjustment to these new organizational conditions across different units within the firm.

[40]The productivity fixed effects are obtained by estimating the AKM model of Equation 1 using productivity (log sales per employee) as the outcome variable over a period of approximately 6 months for the quick service restaurant chain and 18 months for the retailer. It is not possible to estimate the productivity fixed effects for the car manufacturer since the productivity measures (defects per vehicle and total cars produced) are available only at the line level, not at the manager level.

[41]We develop this idea more formally in the stylized model discussed in the next Section.

Average Effects on Production and Absenteeism We begin by estimating the average increase production across all units in the firms following the shocks. We estimate the following regression,

$$Y_{jt} = \sum_{-2 \leq k \leq 2, k \neq -1} D_{jt}^{k} \beta_k + \phi_j + \theta_t + \varepsilon_{jt}, \tag{6}$$

where Y_{jt} is the performance of unit j in period t (pooled across 8 weeks) in terms of production; ϕ_j and θ_t are unit and time fixed effects, respectively. τ_j is the first period when store j experiences the demand shock, $D_{jt}^{k} = 1[t = \tau_j + k]$ for $k \in (-2, 2)$ is the relative time-to-treatment dummy. Finally, standard errors are clustered at the unit level across all specifications.

Figure 8 shows increases in production (impact on the logarithm of cars produced for the car company and the logarithm of transactions for the quick service restaurant chain and retail company) in the first eight weeks immediately after the shock and beyond eight weeks after the initial shock for the three companies.[42] For the car company, the increase in the number of cars produced at the factory level was around 55% in the immediate eight weeks after the shock and 65% after the initial eight weeks. For the quick service restaurant chain, the increase in the number of transanctions was close to 11% in the 8 weeks and afterward. The number of transanctions for the retail company increased by 2% in the immediate eight weeks after the shock and around 4% afterward.

Recall that, to achieve these higher production levels, the firms implemented non trivial changes to the organization of work (i.e., faster pace of work, more multitasking) while keeping wages constant. As we discuss in the stylized model presented in the next Section and in Appendix K, to the extent that these changes increased the cost of workers' effort, this is likely to have moved them to a point in which the marginal rate of substitution between leisure and income does not equal the wage income anymore. One way to get closer to equilibrium and consume more leisure is to be absent for work (Dionne and Dostie, 2007). Consistent with this conceptualization of the effect of the demand shock on workers, in all three companies the increase in production was accompanied by a large increase in absenteeism. Figure 9 shows that a spike in absenteeism is observed both immediately after the production increases and after eight weeks. Following the rapid production ramp up, absenteeism increased by approximately 28% (after eight weeks) for both the car company and the quick service restaurant chain, and around 6-11% the retail company.[43]

Heterogeneity across HT and LT Managers Next, we study whether the effect of the demand shock on production and absenteeism was heterogeneous if the store or unit had an HT manager

[42]Tables F.1-F.3 present the corresponding results presented in Figures 8, 9, and 11.

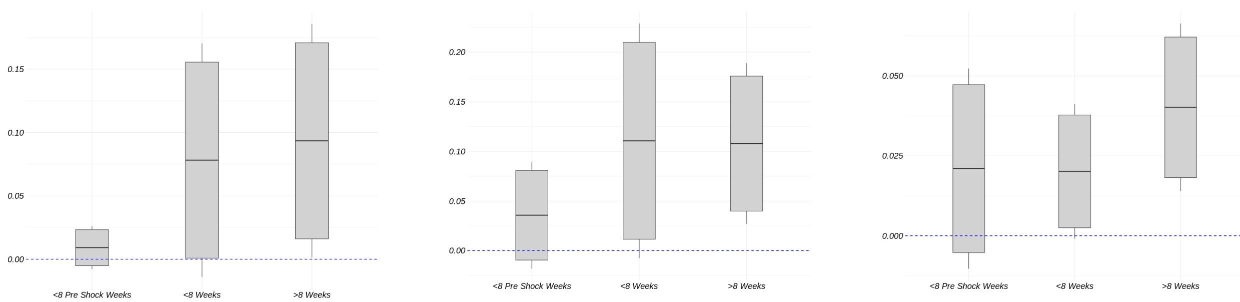
[43]We see a large impact on absenteeism for the car company for two reasons; *i*) the absolute level of absenteeism is low *ii*) the size of the shock is larger.

just before the shock hit the team.[44] To estimate the differential effect of an HT manager before and after the shock, we interact relative time-to-treatment dummies with a dummy variable in Equation 6, setting it to be equal to 1 if the store was supervised by an HT manager before the shock.

Figure 10 summarizes these results.[45] When comparing HT and LT managers, we find that the increase in logarithm of transactions after the shock is slightly higher for HT managers. In the quick service restaurant chain, logarithm of transactions increase by 4.9% on average in stores with HT management, which is 7.94% more than in stores under LT management. This difference becomes more pronounced after the first eight weeks: HT managers maintain higher logarithm of transactions, while the effect of the shock fades for stores with LT management. For the retail company, HT managers see higher logarithm of transactions eight weeks after the shock, but the difference is not significant.

Figure 8: **Increases in Production after the Demand Shock**

(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company



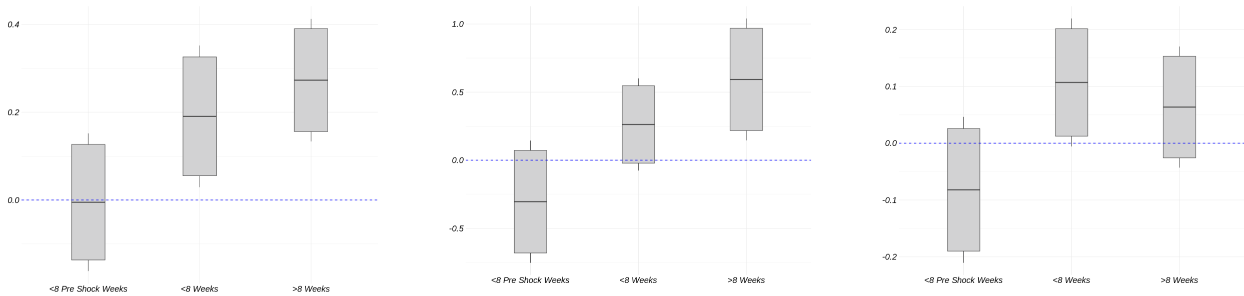
Notes: Figure 8, panel (a), presents the effect of the two mandated production increases on the logarithm of cars produced. Panels (b) and (c) display the impact of the partnership with the last-mile delivery company on the logarithm of transactions for the quick-service restaurant chain and the retail company, respectively. For the car company, the percentage change is 55%* for the first eight weeks and 65%*** after eight weeks. For the quick service restaurant chain, the effect is 11.6%** for the first eight weeks and 10.7%*** after eight weeks. Finally, for the retail company, the effect is 2%** in the first eight weeks and 4%*** after eight weeks. Standard errors are clustered at the unit level. The bars in the graph represent the 90% confidence intervals, while the lines indicate the 95% confidence intervals. *** p<0.01, ** p<0.05, * p<0.1.

[44] We classify a store as having an HT manager if we see that the HT manager is assigned to the store the month before the shock. For stores with multiple managers, we categorize them based on the predominant manager type during the shock period (i.e., we take the mode).

[45] Unfortunately, we do not have unit/team performance for the car company.

Figure 9: **Increases in Absenteeism after the Demand Shock**

(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company



Notes: Figure 9, panel (a), presents the effect of the two mandated production increases on the percentage change in absent employees. Panels (b) and (c) display the impact of the partnership with the last-mile delivery company on the percentage change in absent employees for the quick-service restaurant chain and the retail company, respectively. For the car manufacturer, the effect for the first eight weeks after the event is 19.06%**, and after eight weeks, 27.30%***. For the quick service restaurant chain, the effect for the first eight weeks after the event is 11.93%, and after eight weeks, 26.97%**. For the retail company, the effect for the first eight weeks after the event is 10.70%* and after eight weeks, 6.37%. Standard errors are clustered at the unit level. The bars in the graph represent the 90% confidence intervals, while the lines indicate the 95% confidence intervals. *** p<0.01, ** p<0.05, * p<0.1.

A reason why HT managers were able to increase production during the shock more than other managers is that they did not experience almost any increase in absenteeism. This is shown in Figure 11, which reports the estimates of Equation 6 using absenteeism as a dependent variable. In the car company, while LT managers see a 39% increase in absenteeism in the immediate eight weeks after a shock, HT managers experience a decrease of 2% in absenteeism on average. Moreover, more than eight weeks after the shock, LT managers see a 50% increase in absenteeism, while HT managers only see a 2% change on average. In the quick service restaurant chain, we observe similar effects in the first 8-week period but important differences in the second 8-week period after the shock, when LT managers experience an increase in absenteeism of 26% while HT managers 2.86%. In the retail company, LT managers see an increase of 33% and 11% in the first and second 8-week periods after the shock. In contrast, HT managers see almost no change in the first 8-week period and an increase of 9% in the second 8-week period after the shock.

Robustness First, we explore the robustness of the results to different definitions of HT and LT managers, using terciles of the fixed effects distribution rather than dichotomous variables. Figure G.1 shows that units managed by managers in the top tercile of the training fixed effects distribution have higher production both in the immediate eight weeks after the shock and beyond eight weeks for the two companies. Likewise, Figure G.2 shows that managers in the top tercile consistently exhibit no increase in absenteeism.

Second, we study the impact of the demand shock and the effect of HT managers on other definitions of absenteeism, such as total absences and the share of employees absent. Figures G.3 and G.4 show similar results to the ones presented in Figure 11 and confirm that the effect on the share of employees absent is driven mainly by LT manager. Moreover, Figure G.4 shows that the size of the effect on the share of employees absent is similar: the effect on absenteeism for LT managers is close to 40% for the car manufacturer, 25% for the quick service restaurant chain, and 35% for the retail company.

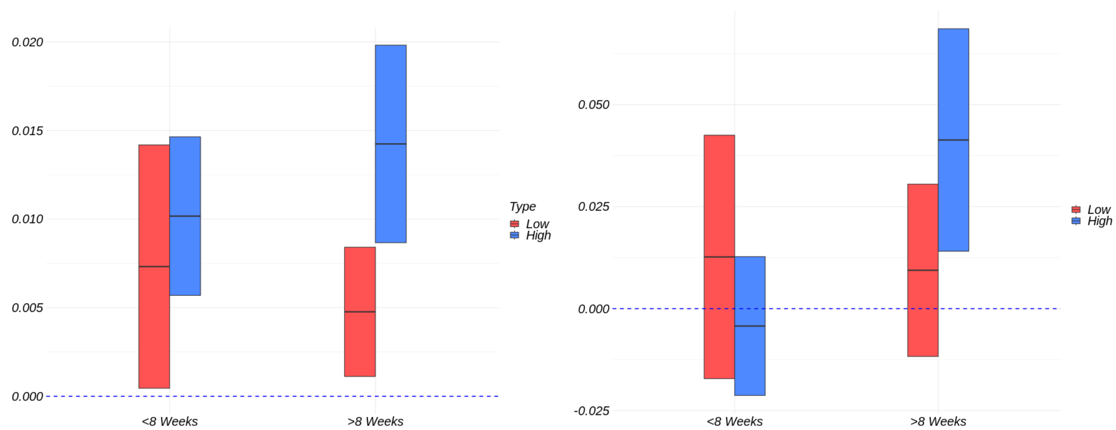
Heterogeneity within and across teams In Section H in Appendix, we study whether the increase in absenteeism was relatively stronger in layers of the hierarchy and occupations that were more likely to experience adjustments after the demand shock, and we then test whether the effect of HT managers could be detected in these more affected sub-units. First, we examine differences between low, middle, and high-ranking workers, as we expected the impact of the demand shock to be relatively heavier for the low-ranked (i.e., frontline employees). Figure H.1 shows that the increase in absenteeism was significantly large among low ranks of the hierarchy, and H.2 shows that the effect is differentially smaller for those that report to HT managers.

Second, we repeat the same exercise distinguishing between different occupations, since some jobs (e.g., cashiers) were more likely to be affected by the change in the pace of production. Reassuringly, we find that the average effect of the shock on absenteeism is significantly higher in occupations that had greater exposure to the demand shock, and that the effect of HT managers is especially visible in these subsets (Figures H.3 and H.4).

Another Shock: Extreme Rainfall Following Bandiera et al. (2018), we study the response to a different type of "shock" that requires workers to exert more uncompensated effort: extreme rainfall. Extreme rainfall significantly increases the effort required for employees to attend work by increasing traffic congestion. Results from this exercise are shown in Section I in Appendix, Figure I.1, where we plot the percentage change in absenteeism in a store after a rainfall shock eight weeks after the shock and beyond for the quick service restaurant chain and retail company. As expected, we find no pre-trends in absenteeism's response to rainfall. Consistently with the results emerging from the demand shocks. we find that an extreme rainfall shock increases absenteeism among LT managers but not HT managers.

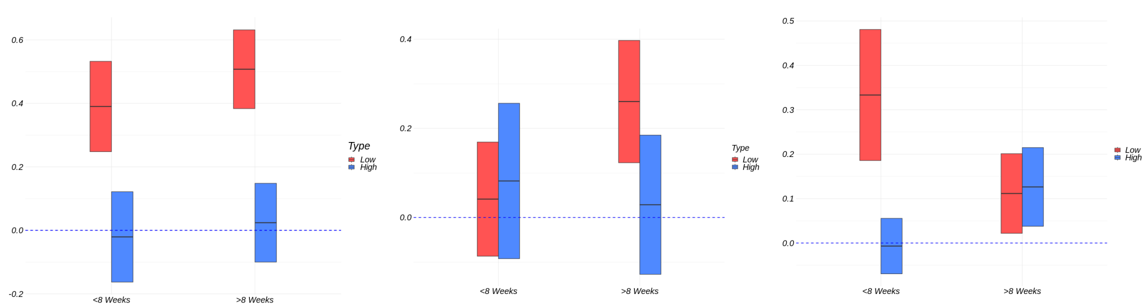
Figure 10: **Effect of the Demand Shock on Performance, by Manager Type (High and Low Training)**

(a) Quick Service Restaurant Chain (b) Retail Company



Notes: Figure 10 shows the impact on the logarithm of transactions for the quick-service restaurant chain and the retail company, both eight weeks after the shock and in the period beyond eight weeks, for high and low training managers. For the quick service restaurant chain, the effect of the LT manager in the first eight weeks is 0.7%; after eight weeks, it is 0.4%. The effect of the HT manager in the first eight weeks is 1%; after eight weeks, it is 1.4%**. Finally, for the retail company, the effect of the LT manager in the first eight weeks is 1.26%; after eight weeks, it is 0.93%. The effect of the HT manager in the first eight weeks is -0.04%; after eight weeks, it is 0.4%. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure 11: **Effect the Demand Shock on Absenteeism, by Manager Type (High and Low Training)**



(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company

Notes: Figure 11 shows the percentage change in absent employees at the unit level, both eight weeks after the shock and in the period beyond eight weeks. For the car company, the LT manager effect in the first eight weeks is 39.03%; after eight weeks, it is 50.76%, while the effect of the HT manager in the first eight weeks is -2.05%**; after eight weeks, it is 2.43%***. For the quick service restaurant chain, the effect of the LT manager in the first eight weeks is 4.12%; after eight weeks, it is 26.01%, while the effect of the HT manager in the first eight weeks is 8.19%; after eight weeks, it is 2.86%*. Finally, for the retail company, the effect of the LT in the first eight weeks is 33.33%; after eight weeks, it is 11.14%, while the effect of the HT manager in the first eight weeks is -0.6%**; after eight weeks, it is 12.62%. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Third, since the demand shock imposed an uncompensated additional cost on workers, we hypothesize that employees' response was also likely to be shaped by their outside options. We proxy for the presence of better outside options using the unemployment rate in the state where stores are located two weeks before the shock. We find that the rise in absenteeism after the demand shock is more pronounced in areas with low unemployment for both the quick service restaurant chain and retail company (Figure H.5). Figure H.6 shows that HT managers experience a lower increase in absenteeism compared to LT managers in low-unemployment states.

5.1 Why do High Training Managers Affect Absenteeism during a Demand Shock?

Workers' Skills HT managers may impact the response to the demand shocks simply through their influence on workers' skills acquisition. That is, since workers reporting to HT managers accumulate more skills, this could help them better adapt to changes in production that make firm-specific skills more valuable. Note that this channel would imply that the mere exposure to HT managers—rather than their presence during the shock—would be sufficient to impact workers' behavior.

To examine this possibility, we proceed in three steps. First, we directly examine whether the change in absenteeism differed between workers who had received more training prior to the shock. To do so, we examine differences between employees above and below the median of the firm's cumulative training participation before the demand shock. Figure J.1 shows no significant impact of the demand shock on absenteeism for high-training employees, whereas we see a strong increase in absenteeism among low-training employees (Figure J.2). Figure J.3 shows that this is exactly the type of workers for which HT managers matter the most.

While the previous exercise suggests that the effect of HT managers on absenteeism is not due to differences in formal training across teams, it does not rule out other possible team confounders that would operate even in the absence of the HT manager while the shock unfolds (e.g. acquisition of informal skills). To examine this possibility, we consider whether the past exposure to an HT manager is sufficient to drive the differential change in absenteeism that we observe in the data, even in the cases in which the HT manager leaves the unit after the shock unfolds. To do so, we compare stores that experience a transition from an HT manager to an LT manager after the shock, and compare them to stores that continuously had an LT manager before and after the shock.[46] We find that just past exposure to an HT manager does not result in differential absenteeism if the manager leaves the unit (Figure J.4). In fact, stores that were previously exposed to an HT

[46]We focus on units where the HT departure happened any time after the shock. Note that in this comparison we exclude from the sample all stores that continuously had at HT before and after the shock. Unfortunately, we cannot run this analysis for the car company, since groups are constructed using the managers as the reference point.

manager experience a large increase in absenteeism 8 weeks after the beginning of the shop in both companies.

Finally, we examine the symmetric case; that is, we estimate Equation 6 on a subset of units that experienced a managerial change from LT to HT six months before the demand shock, and compare them to units that continuously had an LT manager before and after the shock.[47]. This allows us to see whether differences in absenteeism appear even in units that had a relatively short exposure to HT managers before the shock. We see (Figure J.5) that the effects of newly appointed HT managers mimic (qualitatively and quantitatively) the overall effects seen in Figure 11. That is, in the quick service restaurants, units that were recently assigned an HT see smaller increases in absenteeism relative to LT managers 8 weeks after the shock, whereas in the retail company the HT managers experience lower absenteeism within the first 8 weeks after the shock. This suggests that the presence of HT managers, regardless of past skills accumulation, is behind the differences in absenteeism.

Taken together, these results suggest that the marginal effect of HT managers on absenteeism depends on their presence during the shock, rather than solely on workers' skills acquisition or past exposure to HT managers.

Other Managerial Skills and Practices The earlier results suggest that the differences in absenteeism are tightly related to the actual presence of an HT manager. Do HT managers matter because of their support for training or because of other managerial skills or behaviors correlated with their HT status? For example, the effect of HT managers could reflect not their stance on training *per se*, but their productivity, or even perhaps the adoption of other managerial practices correlated with HT status, which may also make workers more resilient to the shock.

To test this idea, we estimate Equation 5 but redefining the dummy variable as an indicator that takes the value of one for high-productivity managers and zero for low-productivity managers (we the productivity fixed effects shown in Figure 7, which are estimated using data prior to the demand shock). We see very little difference in sales for the retail company, and *worse* results for the quick service restaurant chain (see Figure 12). When analyzing absenteeism, high-productivity managers show similar or *worse* outcomes for total absent employees compared to low-productivity managers. Figure 13 shows that in the quick service restaurant chain, high-productivity managers show similar (and positive) change in absenteeism compared to low-productivity managers (red bars) both in the first eight weeks and beyond. In the retail company, high-productivity managers exhibit a significant *increase* in absenteeism within the first eight weeks, which remains higher (though not significantly different) than that of low-productivity managers in the subsequent period. This suggests that the

[47]We include in the analysis units in which the arrival of an HT manager happened any time in the 16 weeks preceding the shock

differential response to the shock does not merely reflect productivity differences across managers.

Similarly, the differential response to the shock could be driven by managerial practices or behaviors correlated with training, rather than managerial value added in training itself. This is a plausible idea since, as we have seen in Section 4.4, HT managers differ from other managers on a number of individual characteristics, as well as in the intensity of adoption of team-oriented management practices. To study this question empirically, we use the subset of the questions presented in Section 4.4 and build an indicator that measures the adoption of "participatory" practices, and examine whether the effects of the demand shock varied across different levels of the index and whether the inclusion of the index accounts for the impact of the HT dummy. We compute the participatory index by taking the principal component of the following measures from the survey: Extraversion, Agreeableness, Reading Mind Rate, Talk Underperformer Worker, and Worker Discuss KPI.[48] The results of this exercise are shown in Tables J.1 and J.2 for the restaurant chain and the retail company, respectively. We find that teams reporting to managers with a high score on the participatory practice index actually experience an increase in absenteeism after the shock. This suggests that the impact of HT managers is unlikely to simply proxy for the adoption of these practices.

What do HT managers do differently? Having established that the impact of HT managers is unlikely to reflect solely workers' skills or correlated managerial attributes, we now turn to examine what happens in stores reporting to HT managers *as the shock unfolds*. We see that these stores differ from others in at least two respects. First, workers get more training during the shock despite having to deal with increased demand. This is shown in Figure 14, which reports the results of the estimation of Equation 6 using training take up as a dependent variable.[49] In the case of the car company, training usually implies removing workers from the production line, which imposes an additional cost. However, we observe a lower reduction in training take up for HT relative to LT managers after the shock.

Second, workers are much more likely to be promoted when they report to HT managers, even during the shock.[50] This is shown in Figure 15: in the car company, teams reporting to HT managers experience a steady increase in promotions, with a 41.82% rise in the first eight weeks and 50.29% afterward. In contrast, teams reporting to LT managers see an 8.95% increase in the first eight weeks and 26.86% afterward. In the quick service restaurant chain, teams led by HT managers see a promotion increase of 5%, whereas we find no significant effect on promotions in the retail company.

[48] Figure J.6, panel (a) and (b) show the distribution of the participatory index for the quick service restaurant chain and the retail company, respectively.

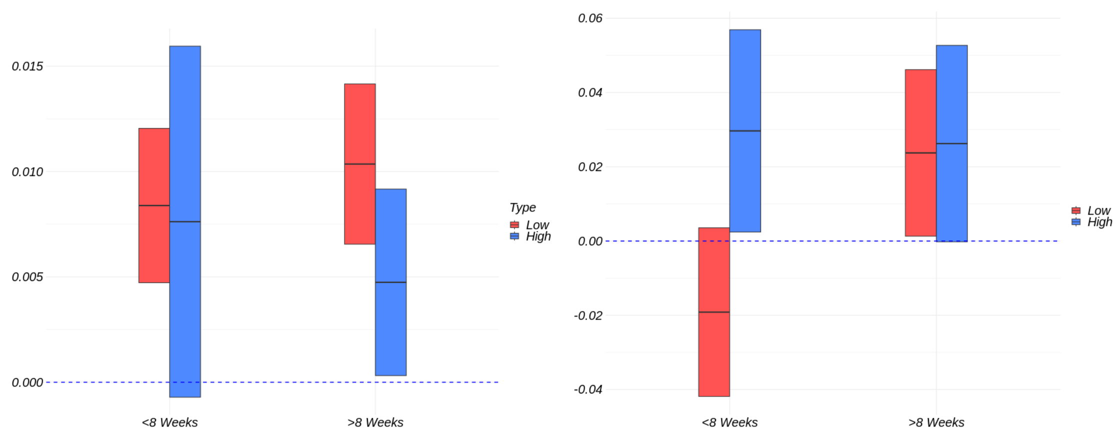
[49] Note that in this regression we exclude all workers hired in the same biweekly period, since they would mechanically receive training as part of their onboarding.

[50] These regressions also exclude all newly hired workers.

Note that we do not find significant differences in terms of hiring decisions (see Figure 16), except for the retail company, where teams reporting to HT managers tend to hire fewer employees than LT managers.

Figure 12: **Effect of the Demand Shock on Performance, by Manager Type (High and Low Productivity)**

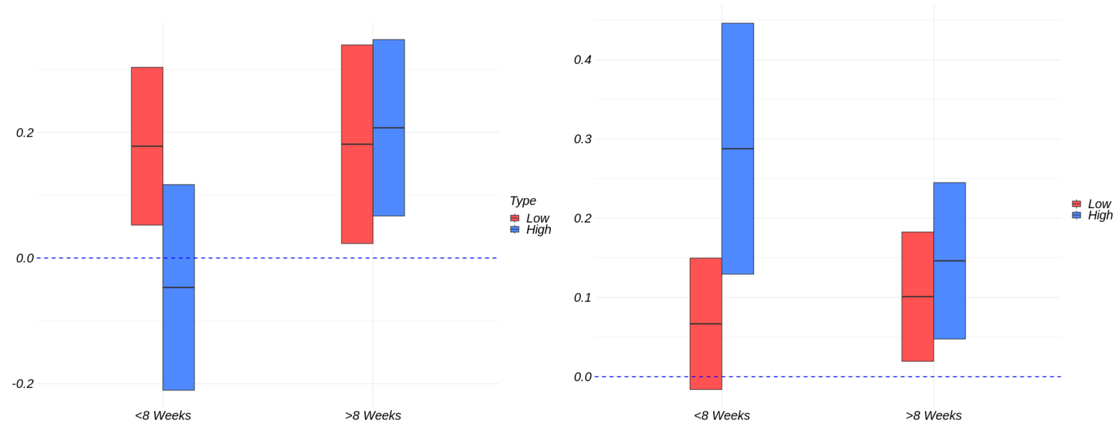
(a) Quick Service Restaurant Chain (b) Retail Company



Notes: Figure 12 shows the impact on the logarithm of transactions for the quick service restaurant chain and retail company, both eight weeks after the shock and in the period beyond eight weeks. We define a manager to be High Productivity if the estimated productivity fixed effect is above the firm median normalizing by connected set. For the quick service restaurant chain, the effect of the Low productivity manager in the first eight weeks after the shock is 2.32%; after eight weeks, it is 1.23%, while the effect of the High productivity manager in the first eight weeks after the shock is 0.97%; after eight weeks, it is 0.55%. Finally, for the retail company, the effect of the Low productivity manager in the first eight weeks after the shock is -1.92%; after eight weeks, it is 2.37%, while the effect of the High productivity manager in the first eight weeks is 2.97%**; after eight weeks, it is 2.62%. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure 13: **Effect of the Demand Shock on Absenteeism, by Manager Type (High and Low Productivity)**

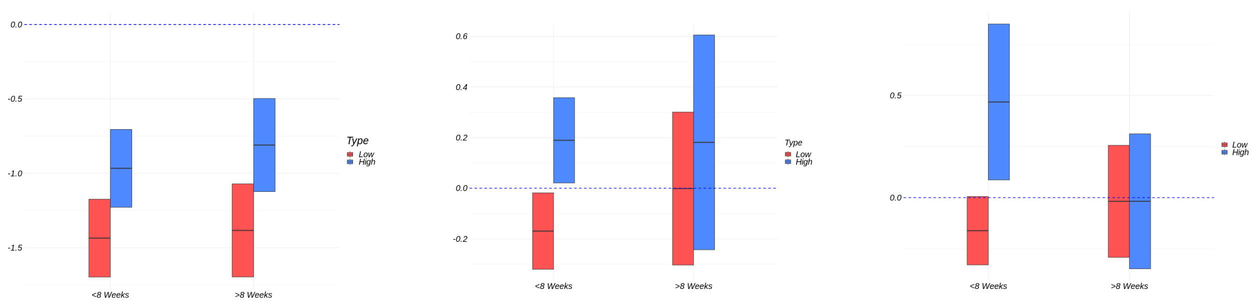
(a) Quick Service Restaurant Chain (b) Retail Company



Notes: Figure 13 shows the percentage change in absenteeism at a store level, both eight weeks after the shock and beyond eight weeks. We define a manager to be High Productivity if the estimated productivity fixed effect is above the firm median by connected set. For the quick service restaurant chain, the effect of the Lowproductivity manager in the first eight weeks is 17.7%; after eight weeks, it is 18.10%. The effect of the High productivity manager in the first eight weeks is -4.6%; after eight weeks, it is 20.7%. Finally, for the retail company, the effect of the Low productivity manager in the first eight weeks is 6.67%; after eight weeks, it is 10.10%, while the effect of the High-productivity manager in the first eight weeks is 28.77%**; after eight weeks, it is 14.62%. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure 14: **Effect of the Demand Shock on Training Takeup, by Manager Type (High and Low Training)**

(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company



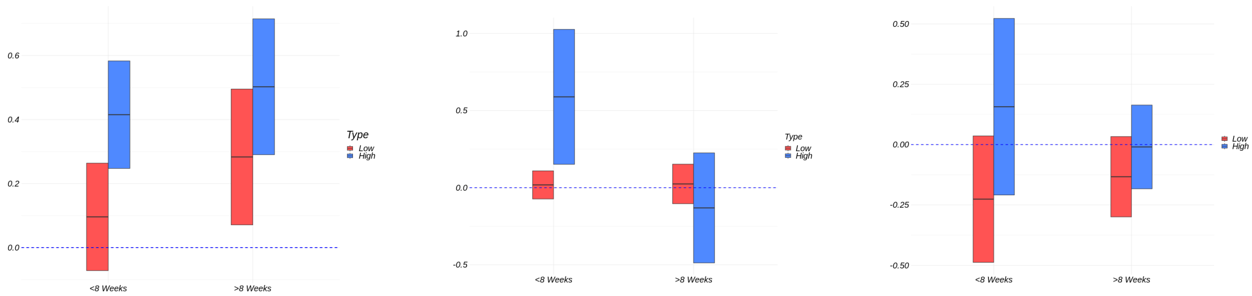
Notes: Figure 14 shows the percentage change in total training take up in a working group (car company) and in a store (quick service restaurant and retail companies), both eight weeks after the shock and beyond eight weeks. For the car company, the LT manager effect in the first eight weeks is -132.27%; after eight weeks, it is -131.67%. The effect of the HT manager in the first eight weeks is -84.95%*; after eight weeks, it is -84.57%*. For the quick service restaurant chain, the effect of the LT manager in the first eight weeks is -18%; after eight weeks, it is 0%, while the effect of the HT manager in the first eight weeks is 19%**; after eight weeks, it is 18%. Finally, for the retail company, the effect of the LT manager in the first eight weeks is -16.22%; after eight weeks, it is -1.83%, while the effect of the HT manager in the first eight weeks is 46.86%**; after eight weeks, it is -1.81. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure 15: **Effect of the Demand Shock on Promotions, by Manager Type (High and Low Training)**

(a) Car Manufacturer

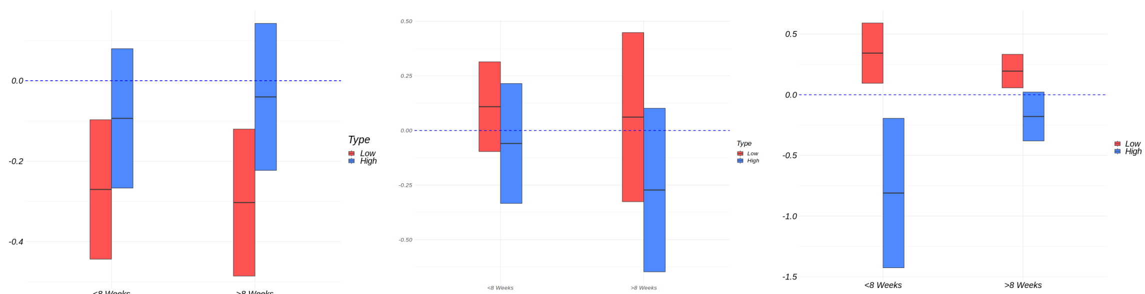
(b) Quick Service Restaurant Chain

(c) Retail Company



Notes: Figure 15 shows the percentage change in promoted employees in a working group (car company) and in a store (quick service restaurant and retail companies) eight weeks after the shock and the impact observed beyond the eight weeks. For the car company, the LT manager effect in the first eight weeks is 8.35%; after eight weeks, it is 26.86%, while the effect of the HT manager in the first eight weeks is 41.82%*; after eight weeks, it is 50.29%. For the quick service restaurant chain, the effect of the LT manager in the first eight weeks is 5%; after eight weeks, it is 8%, while the effect of the HT manager in the first eight weeks is 55%**; after eight weeks, it is -15%. Finally, for the retail company, the effect of the LT manager in the first eight weeks is -22.59%; after eight weeks, it is -13.30%, while the effect of the HT manager in the first eight weeks is 15.70%; after eight weeks, it is -0.96%. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure 16: **Effect of Demand Shock on Hiring, by Manager Type (High and Low Training)**



(a) Car Manufacturer

(b) Quick Service Restaurant Chain

(c) Retail Company

Notes: Figure 16 shows the percentage change in total hiring in a working group (car company), and in a store (quick service restaurant and retail companies), both eight weeks after the shock and beyond eight weeks. For the car company, the LT manager effect in the first eight weeks is -27%; after eight weeks, it is -31%, while the effect of the HT manager in the first eight weeks is -9%; after eight weeks, it is -4%. For the quick service restaurant chain, the effect of the LT manager in the first eight weeks is 10%; after eight weeks, it is 6%, while the effect of the HT manager in the first eight weeks is -4%; after eight weeks, it is -27%. Finally, for the retail company, the effect of the LT manager in the first eight weeks is 34.28%; after eight weeks, it is 19.49%, while the effect of the HT manager in the first eight weeks is -81.03%**; after eight weeks, it is -17.92%**. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Overall, these findings suggest that the impact of HT managers is related to specific managerial decisions related to employees that occur during the shock—including more training and more promotions—while keeping the teams composition constant.

5.2 Summary of Results

In the aftermath of a demand shock that requires workers to adapt to new production conditions without a commensurate increase in wages, HT managers increase production without a significant increase in absenteeism. The large increase in absenteeism after the demand shock suggest that the adjustments needed to cope with the demand shock imposed a cost on employees, but also that this cost was relatively more muted for workers reporting to HT managers. We show that the presence of (vs. past exposure to) HT managers is necessary for the effects on absenteeism to occur, and that these effects do not merely reflect past skills accumulation, or the use of management practices related to training.

6 Model

In Appendix Section K, we show a stylized model in the spirit of Prendergast (1993) to interpret the empirical results presented so far within a single coherent framework.

The firm is modeled as a continuum of organizational units (which can be thought as different teams or stores) staffed by homogeneous workers under the supervision of different middle managers, rather than as a single entity. Within each of these units, workers have the option to invest in the acquisition of firm-specific skills (at a cost) to increase their odds of being promoted to higher-paid occupations including tasks requiring these skills. Where existing models of firm training typically treat promotions as if they were an organization-wide policy, we explicitly allow that promotions might only materialize if the local manager endorses the worker's candidacy. That is, within this decentralized structure, each worker's decision to undertake training depends not only on the associated training cost and the potential wage increase associated with the promotion to a "difficult" job, but also on the specific manager to whom they are assigned. In particular, rather than being equally credible for all employees, the firm's promise of higher wages for skilled jobs depends on the manager's type. This reflects, for example, differences in how managers communicate or advocate promotions.[51]

The result of this within-firm variation is that, for a given wage structure, some teams see no training because employees distrust that promotions will materialize, while others have high training

[51] Middle managers may differ in their mentoring skills (e.g. whether they possess "people skills," as in Hoffman and Tadelis (2021)), and/or their private incentives to support employees' growth and career mobility (e.g. whether they engage in "talent hoarding" as in Haegele (2022))

uptake. This divergence between top management's stated wage policy and a local manager's effective gatekeeping has not, to our knowledge, been explicitly modeled or tested in prior empirical research on training. We embed this set up in a standard labor supply model in which, after deciding whether to train or not, workers determine the number of hours they are willing to work based on their job-specific wages. The firm, in turn, designs an optimal wage structure to incentivize workers to both train and work, accounting for the distribution of managers across the organization.

The basic model illustrates the main trade-off faced by the firm: while having a higher share of trained workers always increases production, incentivizing training through wage increases has diminishing returns on profitability and, above a certain threshold, may even decrease it. This trade off is even starker when the firm faces high training costs, since these reduce the benefits of wage increases. The existence of this trade off is what makes HT managers (that is, managers who amplify the perceived expected value of training among workers) valuable to the firm–they increase training take up for an given and homogeneous wage structure and workforce.

We then extend this basic set-up to study the predicted impact of the demand shock, which we model as an exogenous increase in the fraction of tasks in production requiring trained workers. The model shows that, in the long run, the firm will respond to the shock by increasing the wage margin between jobs for trained relative to untrained workers. Before this wage adjustment occurs, however, the firm will cope with the demand shock by requiring existing employees to exert more effort, for example increasing their number of contracted hours for a constant wage. This will have two short-run implications. First, to the extent that the increase in contracted hours pushes workers above their optimal hours, this change will result in a higher probability of workers engaging in absenteeism–that is, workers leverage absenteeism to get closer to their optimal hours. Second, the anticipation of a wage increase will lead more workers into training.

The key comparative static we derive is that managers who support training–that is, who are able to convey a higher probability of promotion conditional on training—will see a smaller increase in absenteeism relative to others. This is due to two distinct channels. First, because these managers have on average a higher share of trained workers, and these workers are more likely to be assigned to difficult jobs and be paid higher wages. Second, since the promise of a future wage increase is relatively more credible for workers reporting to supportive managers, this will translate in higher training take us as the shock unfolds. This implies that the firm's ability to whether the demand shock can increase dramatically if managers are more supportive of employees' career prospects—even holding the wage gap constant.

More broadly, the model suggests that if a policymaker or headquarters tries to raise skill formation solely by raising wages for skilled jobs, they may face diminishing returns once it becomes too costly. Instead, having more HT managers can boost training at the same wage margin. This insight suggests a more cost-effective path to skill accumulation might be managerial screening or training managers themselves, an angle rarely considered in standard firm-sponsored training models.

7 Conclusions

We provide new evidence showing that middle managers play a critical role in the effective implementation of internal training programs within firms. By analyzing detailed administrative data from a car manufacturer, a quick service restaurant chain, and a retail company in Latin America, we show that there exist wide variation on middle managers' value added in employees' training take-up. Hight-Training managers—that is, those that are above the company median in training value added—managers are distinct in their focus on team development and employee engagement, compared to low-training (LT) managers, who emphasize individual high performers. We also show that these differences matter for firm performance. Namely, teams led by HT managers experience better engagement and lower absenteeism, particularly during periods of organizational change.

Our findings imply that simply offering training subsidies or designing more elaborate internal training curricula may be insufficient if managers on the ground do not effectively champion the program. For companies, an equally important priority is to identifying and incentivize middle managers who reliably promote training. Including middle managers into the design and execution of training programs and designing incentive contracts compatible with these tasks may significantly enhance their effectiveness and contribute to overall firm productivity. For policymakers, our results raise caution that top-down skill mandates might be ineffective without local buy-in. Therefore, the design of training policies is likely to require a more in depth understanding of how organizational frictions could interact with—and possibly undermine—the desired policy objectives.

Future research should continue to explore the long-term impacts of middle managerial practices on training take-up and employee career advancement. If local managerial buy-in is critical to effective training, an open question is whether firms can systematically develop high-training managers. Future work could assess whether systematically reshaping managerial incentives—e.g., tying part of the manager's bonus to employee skill certification and promotion—could amplify training take-up further. Our evidence suggests large potential returns from better aligning middle managers with central HR strategies. Another promising area of research is how to design screening mechanism to identify managers who actively support training. We leave these topics for future research.

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ONLINE APPENDIX

A Institutional Details

A.1 Organization of Production

Table A.1: Organization of production

	Car Company	**Quick Service Restaurant Chain**	**Retail Company**
Country	Argentina	Colombia	Colombia
Company description	Automobile assembly plant. Organization within each team: 1 manager, 3 mid-line operators and 16 front-line operators.	Restaurant. Within each restaurant: 5 customer touchpoints across 39 stations.	High-scale retailer. Functions: customer service, product replenishment and display, cashier and payment, logistics and storage, security, and administrative support.
N. of employees	2,476	2,500	25,429
Number of units	2 (Trim and Chassis)	52 stores	83 stores
Number of managers	196	492	277

A.2 Role of Middle Managers

Car Company The basic unit of production within the single plant is a working group, generally comprising of one middle manager, 3 mid-line operators, and 16 front-line operators, although this structure has occasional variations. Each working group assembles a specific part of the vehicle on a production line and is led by a middle manager (internally defined as the ”group leader”). This figure plays a pivotal role in supporting and managing the overall performance of their working groups, to maintain efficiency and quality in the production line. The middle manager is involved in a wide range of tasks, e.g. ensuring that production processes run smoothly, coordinating activities among team members, and addressing issues that arise during production. Most of the middle managers are internally promoted (typically from team members, to team leaders and finally to group leaders) and have undergone extensive and comprehensive training programs. Managers receive a base salary.

Quick Service Restaurant Chain In each of the restaurants, middle managers ("Store managers") are responsible for overseeing operations, leading teams across multiple shifts and various stations. Each store can have between one to six managers and around 23 workers at any point in time. Store managers play a critical role in the restaurant's performance by monitoring workflow, detecting and addressing major issues, and maintaining service pace. Their specific duties include ensuring efficient daily operations, calibrating equipment, maintaining sanitation, managing inventories, conducting final product quality checks, minimizing waste, and handling personnel management tasks such as employee scheduling, recruitment, and training. Store managers undergo extensive training, starting as crew members and progressing through a series of certifications and specialized courses. Managers receive a base salary with a portion tied to store performance.

Retailer Middle managers (also "Store managers") oversee the entire store's operations, leading teams of approximately 115 people across multiple shifts and sections. Each store can have up to three managers. Store managers are responsible for personnel management, inventory management, product displays, price changes, and promotions. Managers receive a base salary with a significant portion tied to store performance. They are trained in various store sections and support section leaders, review inventory, and analyze store and product performance. Managers conduct daily meetings with general managers and section leaders to discuss performance metrics and strategies. They also check local competitor prices and address any inventory issues.

A.3 Training

Car Manufacturer Most new employees start as frontline (FL) workers, and they are onboarded to get basic skills required for entry-level positions.[52] Workers are promoted as they gain experience, complete specific training programs, and develop new job skills necessary for each layer of advancement (Adhvaryu et al., 2023a). Training is provided in-house and focuses primarily on management, problem-solving, and aligning production line activities with company targets rather than just technical skills. More advanced training programs emphasize problem-solving and management skills, with a significant portion of courses dedicated to these topics for promotions to team leader and group leader or manager positions. Workers frequently receive training before commencing their roles, and production halts for training purposes are common.

Quick Service Restaurant Chain There are three major types of training programs: (i) training provided to new workers in a new skill, (ii) training of existing workers in new skills, and (iii) refresher training provided to workers who are already certified in certain skills in order to re-up

[52] For example, basic production skills.

their practice in those areas (Adhvaryu et al., 2023b, 2022). Each training program comprises a specific number of modules that the worker must complete and pass. These evaluations take place during regular shifts in the store. New workers go through a set of training programs that include modules about basic principles such as customer service, production skills (covering at least three kitchen stations), and complementary skills programs. Refresher training is provided to ensure crew members maintain their skills. The goal is for each crew member to undergo refresher training and be re-evaluated on at least one station per month, ensuring ongoing competency and proficiency.

Retailer Training programs serve multiple purposes: introducing workers to their roles and sectors and providing ongoing training when new processes, products, or technologies are introduced in the store. Both lateral and vertical moves within the company strongly encourage the completion of relevant training programs; however, they are not required and sometimes not necessary for the success of operations in the store. Most of the training is on-the-job, meaning that workers are trained during regular working hours while actively performing specific tasks. Additionally, the company offers virtual and face-to-face instructional programs, which differ from on-the-job training by featuring more structured learning modules, including tests and a teaching component. These types of training programs primarily focus on safety, product management, and customer service.

B Robustness of the AKM model

Sorting on training or productivity We follow Card et al. (2013) and Adhvaryu et al. (2020) and conduct an event study around moves to determine whether these moves are systematically driven by sorting on the match-specific component of training. We isolate movers in our data and then rank them based on: (i) quartiles of the average training of the store they moved away from; and (ii) quartiles of the average training of the store they moved to. Figure B.1 plots the average biweekly residual training takeup of the movers on the y-axis.[53] This is computed for more than 4 weeks (period= -2) and 1 to 4 weeks (Period = -1) before the move from the origin store, and 1 to 4 weeks (Period = 1) and more than 4 weeks (Period = 2) after the move to the new destination store, as shown on the x-axis. The plot is divided by quartiles of the average training of the origin and destination stores. To simplify the graph, we only show moves away from stores in the top quartile of average training (quartile 4) or the bottom quartile of average training (quartile 1).

In the graph, we observe that movers in the lower quartiles (specifically quartiles one and two) tend to show a higher residual or improvement when moving to a higher quartile (specifically quartiles three and four). Conversely, movers transitioning from higher quartiles (quartiles three and

[53]To calculate the training residuals, we perform a regression of training on year and biweekly period fixed effects.

four) to lower quartiles (quartiles one and two) exhibit a decrease in residuals for both companies. Movers transitioning between similar quartiles show minimal changes, remaining relatively constant throughout the sample period, as seen in Figure B.1.[54]

Figure B.3, movers are ranked based on quartiles of average training in their initial store with average training computed over the entire sample period and quartiles calculated for each store, as in Figure B.1. The figure then plots the average change in residual training for movers from quartile X to quartile Y against the change in residual training for movers in the opposite direction.[55] The changes are calculated based on average residual training in the eight weeks before and after the move. The solid line represents the 45-degree line, indicating perfect symmetry. In Figure B.3 shows that moving to a store/manager with higher training levels generally results in a gain in training, while moving to a store with lower training levels results in a loss in training. Most of these gains and losses appear symmetric. For instance, moves from quartile four to quartile two result in changes that mirror those from quartile two to quartile four. This overall symmetry supports our identification assumptions, despite small deviations from the symmetry line that appear to be non-systematic for each of the three companies.

To test for endogenous mobility based on productivity, we conduct a similar analysis to that in Appendix B.1, using log(sales/number of employees) as the variable of interest. Figure B.2 presents similar characteristics to our training analysis, suggesting a symmetric relationship with respect to productivity. Similar to our symmetry test for training (Figure B.3), we perform a symmetry test for our productivity measure. We find evidence that our data points fit the 45-degree line reasonably well, providing additional evidence for the independence of the error term and our productivity measure. Results are summarized in Figure B.4.

Pretrends We check whether the training trend of movers at the initial store—the store from which they move—exhibits systematic trends in the days just before the move. Figure B.1 reveals that while the residual training before the move does exhibit some changes in the periods before the move, these changes do not seem to be systematically related to whether the manager moves to a high-training or low-training store.

Furthermore, there is no clear direction in the trends prior to the move. Managers in high quartile stores show both positive and negative training trends before the move, similar to managers in low-training quartiles. This lack of systematic trends supports the assumption of conditional exogenous mobility, indicating that the training trends of movers are not systematically related to

[54] As discussed in Card et al. (2013), if moves are conditionally mean independent of the match-specific component, the gains from moving from store (or manager, in the case of the car company) X to store/manager Y should be equal and opposite to the losses from moving from store/manager Y to store/manager X. In other words, the gains and losses for movers should be symmetric.

[55] For example, the point labeled "2 to 4, 4 to 2" shows the average change for movers from quartile 2 to quartile 4 plotted against the change for movers from quartile 4 to quartile 2.

their subsequent moves to higher or lower training stores.[56]

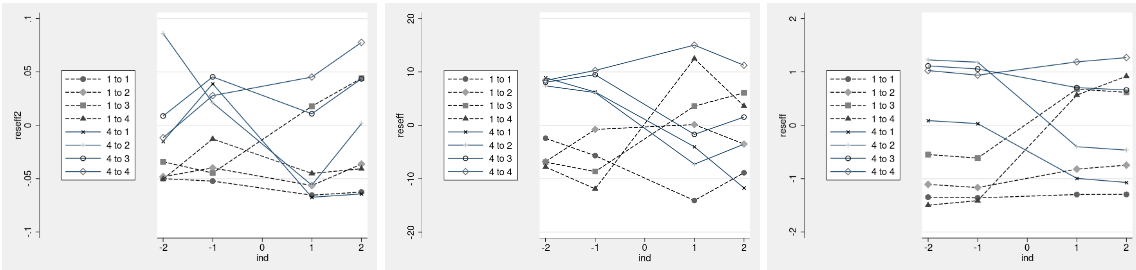
Limited mobility bias Finally, we test for limited mobility bias, which arises when there are relatively few movers in the data, leading to biased estimates of the correlation between worker and firm effects (Abowd et al., 2004; Andrews et al., 2008, 2012). The identification of both manager and store fixed effects in the AKM model requires observing a sufficient number of managers over time in different stores, ensuring adequate mobility. For the car company, this process also involves tracking workers under various managers and observing each manager with multiple different workers. If the number of movers across units is limited, we can not separately identify the unit and manager fixed effects.

To address the issue, we implement several tests. First, notice that our results indicate that there is substantial mobility among workers (in the car company) and managers (in the quick service restaurant chain and retail company). That is, 69.56% of managers move at least once for the car company, and 49.67% and 46.22% of managers move between stores at least once for the retail and quick service restaurant companies, respectively. The level of mobility observed within this context is significantly higher than that reported in inter-company statistics. As a comparison, the share of worker movers across firms is around 12% in Andrews et al. (2012), 25% in Card et al. (2013), and around 35% in Alvarez et al. (2018). Second, we note that the number of observations per manager and per store (or worker in the case of the car company) is much larger than in typically matched employer-employee (MEE) datasets. On average, each biweekly period, the car company has 15 employees per working group, the quick service restaurant chain has 23 workers per store, and the retail company has 115 employees per store. Accordingly, concerns regarding limited mobility bias are limited in our setting. Nevertheless, as a robustness check, we perform the bias correction procedure suggested by Andrews et al. (2008), which is standard in the literature. Second, we allow for heteroskedasticity by following the leave-out estimation of Kline et al. (2020). These results are reported in the Table B.1. Table B.1 presents the variance of worker effects (Var(θ)), the variance of firm effects (Var(ψ)), and the covariance (Cov(ψ,θ)) and correlation (Corr(ψ,θ)) between these effects for three datasets.[57] Despite slight differences in the covariance measure that show an existing but small bias in the direction that B.1 anticipates, the main results are largely robust across all correction methods implemented.

[56]The productivity analysis yields consistent results. There is no evidence of systematic pretrends in productivity prior to the move.

[57]The results show that the baseline method tends to overestimate variances and underestimate correlations compared to the bias-corrected methods of Andrews et al. (2008) and the leave-out estimator. For instance, in the car manufacturer dataset, the leave-out estimator reveals a stronger negative correlation between worker and firm effects compared to the baseline. Similar patterns are observed in the quick service restaurant chain and retail company datasets.

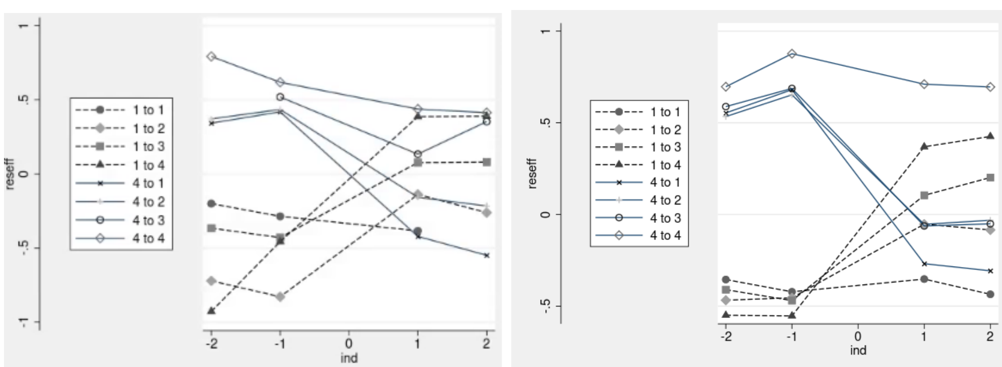
Figure B.1: Event Study Around Movers - Training



(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company

Notes: Figure B.1 presents an event-study analysis of employee moves across stores, focusing on differences in average training levels. Movers are classified based on (i) the quartile of average training in their origin store and (ii) the quartile of average training in their destination store. Average training is computed over the full sample period, and quartiles are assigned at the store level. To construct the outcome variable, we first regress biweekly training at the working group level (i.e., car in the car company; store in the quick service restaurant and retail companies) on year and biweek fixed effects. The residuals from this regression (denoted as resseff) represent deviations from the expected training level and their predictions over the x-axis periods are shown on the y axis. On the x-axis, we depict periods relative to the move: Period = –2 corresponds to more than four weeks before the move; Period = –1 captures one to four weeks before; Period = 1 represents one to four weeks after the move; and Period = 2 corresponds to more than four weeks after the move. The y-axis shows the average residual training for movers. The figure emphasizes movements from and to stores in the top (Q4) and bottom (Q1) quartiles of the training distribution. Each line represents a specific move type (e.g., 1 to 2 denotes a move from a store in the first quartile to one in the second quartile).

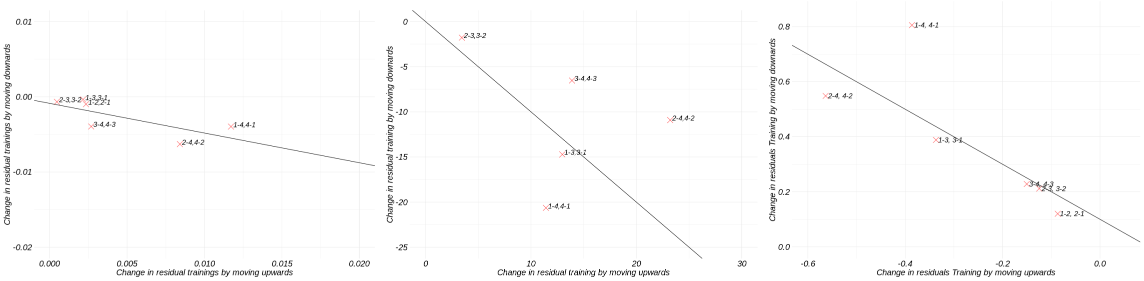
Figure B.2: Event Study Around Movers - *log*(Productivity)



(a) Quick Service Restaurant Chain (b) Retail Company

Notes: Figure B.2 ranks movers in terms of (i) quartiles of average productivity in their initial store and (ii) quartiles of the average productivity in the store where they moved to. The average productivity is computed over the entire sample period, and quartiles are calculated at the store level. The graphical representation depicts the average residual productivity (reseff) of movers on the y-axis; the residual is predicted for specific periods: more than 4 weeks (Period = -2) and 1 to 4 weeks (Period = -1) before the move from the initial store, and 1 to 4 weeks (Period = 1) and more than 4 weeks (Period = 2) after the move to the new destination store, plotted on the x-axis. The analysis focuses on moves away from stores in the top quartile (lines in quartile 4) and stores in the bottom quartile (lines in quartile 1). To create the residual variable, we run a regression of the biweek productivity of each store, on year and biweek fixed effects. Then we predict the residuals and run the movers analysis.

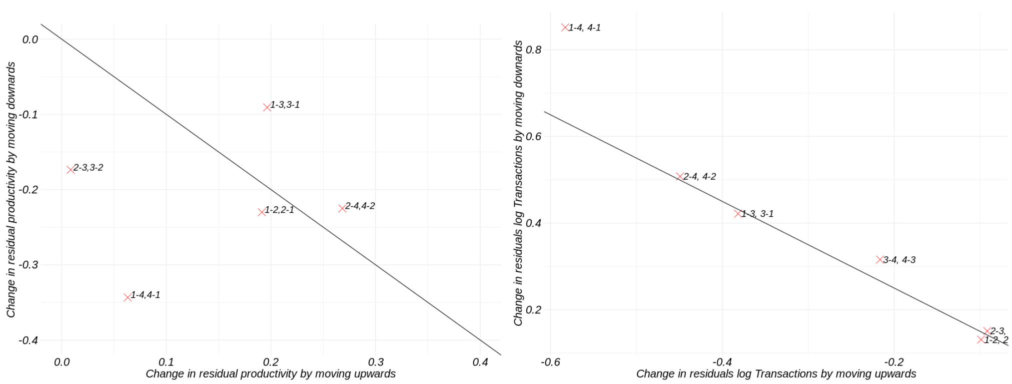
Figure B.3: Symmetry Test - Training



(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company

Notes: Figure B.3 ranks movers in terms of (i) quartiles of average training in their initial store and (ii) quartiles of the average training in the store where they moved to. The average training is computed over the entire sample period, and quartiles are calculated for each store. The Figure then plots the average change in residual training of movers from lines in quartile X to quartile Y, against the change in residual training for movers in the opposite direction; for example, the point labeled "2 to 4, 4 to 2" corresponds to the average change for movers from lines in quartile 2 to quartile 4, plotted against the change for movers from lines in quartile 4 to quartile 2. The changes are calculated for average residual training in the eight weeks before the move and the eight weeks after the move. The solid line corresponds to the 45-degree line. To calculate the training residual, we run a regression of total training done in the working group (car company) and stores (quick service restaurant and retail companies) each biweek, on year and biweekly fixed effects. Then, we predict the residuals and run the movers analysis.

Figure B.4: Quick Service Restaurant Chain and Retail Company: Symmetry Test - *log*(Productivity)



(a) Quick Service Restaurant Chain (b) Retail Company

Notes: Figure B.4 ranks movers in terms of (i) quartiles of average productivity in their initial store and (ii) quartiles of the average productivity in the store where they moved to. The average productivity is computed over the entire sample period, and quartiles are calculated for each store. The Figure then plots the average change in residual log sales of movers from lines in quartile X to quartile Y, against the change in residual productivity for movers in the opposite direction; for example, the point labeled "2 to 4, 4 to 2" corresponds to the average change for movers from lines in quartile 2 to quartile 4, plotted against the change for movers from lines in quartile 4 to quartile 2. The changes are calculated for average residual log sales in the eight weeks before the move and the eight weeks after the move. The solid line corresponds to the 45-degree line. To calculate the log sales residual, we run a regression of productivity in the stores on year and biweekly fixed effects. Then, we predict the residuals and run the movers analysis.

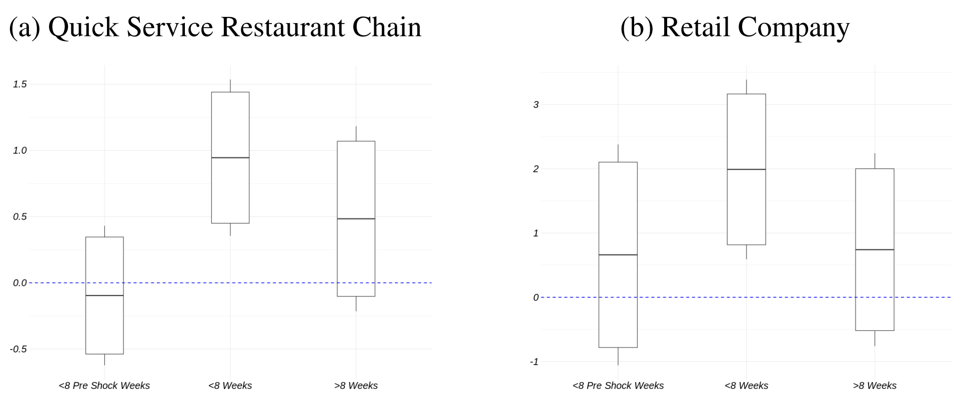
Table B.1: Limited Mobility

	Baseline	Andrews et al. (2008)	Leave-out Estimator
		Car Manufacturer	
Var(θ)	0.036	0.030	0.021
Var(ψ)	0.028	0.025	0.021
Cov(ψ,θ)	-0.026	-0.023	-0.020
Corr(ψ,θ)	-0.832	-0.851	-0.941
		Quick Service Restaurant Chain	
Var(θ)	1.944	1.892	1.949
Var(ψ)	0.135	0.071	0.130
Cov(ψ,θ)	-0.157	-0.097	-0.162
Corr(ψ,θ)	-0.306	-0.286	-0.322
		Retail	
Var(θ)	0.818	0.381	0.488
Var(ψ)	1.529	1.126	1.236
Cov(ψ,θ)	-0.746	-0.386	-0.485
Corr(ψ,θ)	-0.667	-0.589	-0.624

Notes: Table B.1 reports the baseline model which comes from the estimation of equation (1) following Abowd et al. (1999), the bias correction of Andrews et al. (2008) and leave-out Estimator from Kline et al. (2020). The data for the car company spans over January 2017 to October 2019 through 196 working groups; for the quick service restaurant chain, the analysis is done between June 2018 and November 2019 for 52 stores. Finally, the study for the retailer company is conducted for 83 stores from January 2017 to March 2020. For each model we compute the variance of the training take-up variable, the variance of the manager fixed effects $var(\theta)$, the variance of the working group (car company) stores (quick service restaurant and retail companies) fixed effects $var(\psi)$, and the correlation $Corr(\psi,\theta)$ and covariance $Cov(\psi,\theta)$ of both type of fixed effects. The results are robust to all model specifications.

C Portability Results using split samples

Figure C.1: Arrival of a High Training Manager and Workers' Training Take up for the split sample.



Notes: Figure C.1 shows the percentage change in training take-up after the arrival of a HT manager to a store previously under a LT manager. We define HT manager as a manager with a fixed effect above the 50 percentile of the distribution by connected set. Fixed effects are calculated for the periods before shocks that increase demand for each store within each company. For the quick service restaurant chain, the effect in the first eight weeks is 95%***, and after eight weeks, it is 48%. Finally, for the retail company, the effect in the first eight weeks is 200.02%***, and after eight weeks, it is 90.44%. Standard errors are clustered at the unit level. The bars in the graph represent the 90% confidence intervals, while the lines indicate the 95% confidence intervals. *** p<0.01, ** p<0.05, * p<0.1.

D Training Specialization and Team Composition

Table D.1: High vs Low-Trained Employees

	Car Manufacturer			Quick Service Restaurant Chain			Retailer		
	Low-Trained	High-Trained	p-value (Difference)	Low-Trained	High-Trained	p-value (Difference)	Low-Trained	High-Trained	p-value (Difference)
Total Training	0.021	0.369	0.000	7.246	10.627	0.000	0.016	0.126	0.000
Experience (Years)	7.264	6.082	0.000	1.61	1.72	0.000	4.362	4.65	0.06
Age (Years)	-	-	-	25.96	26.41	0.000	-	-	-
Gender($\frac{Male}{TotalEmployees}$)	-	-	-	0.739	0.567	0.000	0.234	0.442	0.000

Notes: Table D.1 presents the differences between low- and high-trained employees across various demographic variables. A high-trained employee is defined as one who is trained more than the median of the store. For the car manufacturer, age and gender are not available.

Table D.2: Employees Demographics by Manager Type

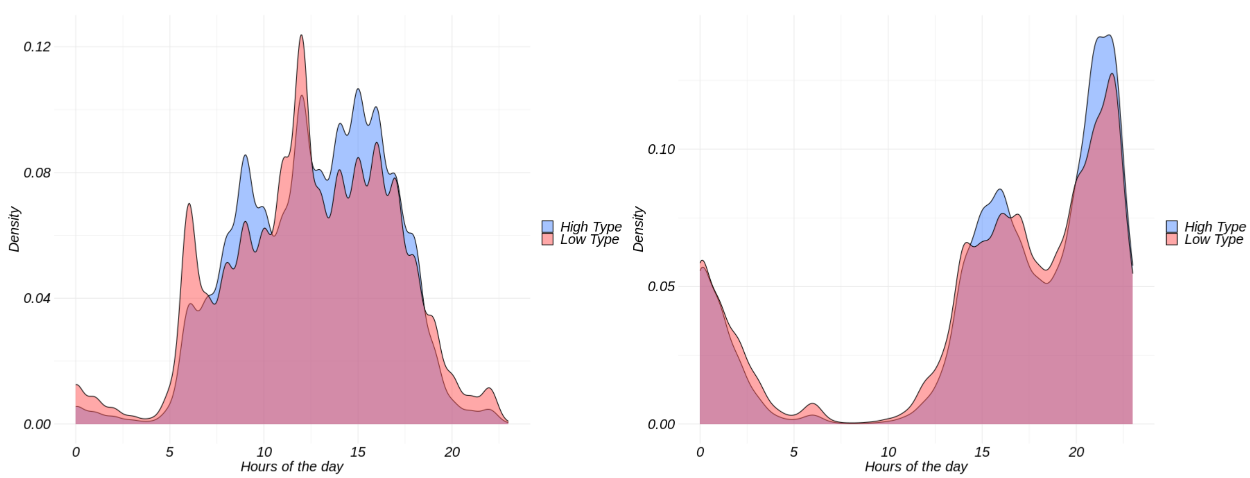
	Car Manufacturer			Quick Service Restaurant Chain			Retailer		
	Low Training Manager	High Training Manager	p-value (Difference)	Low Training Manager	High Training Manager	p-value (Difference)	Low Training Manager	High Training Manager	p-value (Difference)
Experience (Years)	8.81	10.05	0.000	1.40	1.51	0.000	5.62	6.06	0.23
Age (Years)	-	-	-	25.42	25.92	0.254	-	-	-
Gender($\frac{Male}{TotalEmployees}$)	-	-	-	0.538	0.537	0.569	0.398	0.424	0.195

Notes: Table D.2 shows the differences in various demographic variables of employees supervised by HT and LT managers, including experience, age, and gender. Age and gender data are unavailable for the car manufacturer.

D.1 Shifts by Manager Type

Figure D.1: Shifts by Manager Type

(a) Arrival Hour (b) Hour to Leave Work



Notes: Figure D.1 plots the density graph of the HT and LT managers' arrival and hours to leave work between 00:00 and 24:59 hours for the **quick service restaurant chain**. There is no significant difference in the distribution of the shifts between the two types of managers.

D.2 Manager Fixed Effects across different HR outcomes

As in equation 1 where we estimate the fixed effects for training, we estimate an AKM model for the following HR outcomes: Absenteeism, Turnover, and Promotions, to estimate the value added by managers, controlling for time and unit fixed effects. Absenteeism is defined as the total number of absent employees, turnover is the total number of retired employees, and the Promotions variable is the number of promoted employees. For the quick service restaurant chain and retail company, we estimate the fixed effects of managers and store managers, while for the car company, we estimate the impact of workers and managers. The sample size of manager fixed effects, which is the same across the three variables, by the company is the following one: 309 managers for the car company, 399 for the quick service restaurant chain, and 416 for the retail company.

E Survey

The survey follows Adhvaryu et al. (2023e) and can be obtained at the following link: **SURVEY**.

E.1 Variable Construction

For each variable in our dataset, we created standardized versions. The standardized variable stdX for any variable X was computed as:

$$\text{stdX} = \frac{X - \bar{X}}{\sigma_X}$$

where $\bar{X}$ is the mean of X and σ_X is the standard deviation of X. This transformation ensures that all variables can be comparable on the same scale.

E.1.1 Individual Characteristics

- **Education:** The survey asked managers to indicate the highest level of education they have attended, offering a range of options from elementary school to graduate studies. Respondents could select from various stages of completion within each educational level, including whether they had completed or not completed elementary school, high school, technical education, college, or graduate studies. A greater value of this variable means a higher level of education.

- **Female Gender:** The survey included a question on gender, where managers were asked to identify themselves as either male or female.

- **Conscientiousness:** The survey assessed managers' levels of conscientiousness through a series of statements, where they were asked to indicate their agreement on a five-point Likert scale ranging from ”Disagree” to ”Strongly Agree”. The statements included behaviors such as being prepared, paying attention to details, completing chores promptly, and maintaining order. Other items focused on following a schedule, being exacting in work, and managing personal belongings. Additionally, the survey explored tendencies to be disorganized, such as making a mess, avoiding duties, and forgetting to return items to their proper places.

- **Extraversion:** The survey evaluated managers' levels of extraversion by presenting a series of statements and asking them to rate their agreement on a five-point Likert scale, ranging from ”Strongly Disagree” to ”Strongly Agree”. The statements assessed various aspects of social behavior and comfort in social settings. Positive indicators of extraversion included statements like ”I am the life of the party”, ”I feel comfortable around people”, and ”I start conversations”. Other items measured the extent to which respondents enjoy social interactions, such as talking to people at parties and being comfortable as the center of attention. Conversely, items like ”I don't talk a lot”, ”I stay in the background”, and ”I am quiet around strangers” were designed to capture introverted tendencies.

- **Agreeableness:** Using a five-point likert scale ranging from ”Strongly Disagree” to ”Strongly Agree”, the statements in the survey assessed various aspects of empathy, compassion, and interpersonal concern. Positive traits associated with agreeableness were measured through items like ”I am interested in people”, ”I sympathize with others' feelings”, and ”I take time out for others”. Other statements, such as ”I feel others' emotions” and ”I make people feel at ease”, further gauged respondents' tendency to be caring and considerate in social interactions. Conversely, negative aspects of agreeableness were captured through items like ”I feel little concern for others”, ”I insult people”, and ”I am not interested in other people's problems”.

- **Openness:** The survey evaluated managers' levels of openness using a five-point likert scale ranging from ”Strongly Disagree” to ”Strongly Agree”, measuring various aspects of intellectual curiosity, creativity, and preference for novelty. Positive indicators of openness included statements like ”I have a rich vocabulary”, ”I have a vivid imagination”, and ”I am full of ideas”. Respondents were also asked about their cognitive abilities, such as being quick to understand things and having excellent ideas. Additionally, the survey explored the use of complex language and the tendency to reflect deeply on topics. Conversely, items like ”I am not interested in abstract ideas”, ”I do not have a good imagination”, and ”I have difficulty understanding abstract ideas” assessed lower levels of openness

- **Locus Control:** Using a five-point likert scale ranging from ”Strongly Disagree” to ”Strongly

Agree", this section explored beliefs related to control over life events and success. A statement like "I believe that my success depends on ability rather than luck" reflects an internal locus of control, where individuals see their actions and abilities as the primary drivers of their success. Conversely, statements such as "I believe that unfortunate events occur because of bad luck", "I believe the world is controlled by a few powerful people", "I believe some people are born lucky", and "I believe in the power of fate" where the managers believe that the success and the accomplishment of goals and objectives depends on external aspects and factors that are not controlled by them.

- **Self Esteem:** The survey using a five-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree", evaluates the self-esteem of each manager. For instance, statements that state good self-esteem for the manager are "I feel that I am a person of worth", "I am able to do things as most other people," and "I feel that I have a number of good qualities", while questions like "I fell I do not have much to be proud of" and "I feel that I am a failure" reflects if there is any low self-esteem in the manager.

- **Raven:** The survey implemented a set of exercises where, based on a figure, the manager should be able to identify the pattern of the figure by selecting one of the multiple options that they have. If the manager identifies the pattern correctly, the raven test will show a greater score for this manager.

- **Reading Mind Rate:** In the same way as the raven test, the survey using figures with peoples' looks, evaluates the ability of the manager to determine the sentiment or feeling reflected in the picture.

- **Arithmetic:** In this section, the surveys ask to the managers to complete a set of basic mathematics exercises such as "$11+17$" or "$36/2$". A greater value in this variable highlights more correct answers.

- **Digital Span Recall:** Given a list of numbers that appears on the screen of the manager for five seconds, the manager should be able to recall the list and write the list in the same order. The surveys start from a list with three numbers, such as "7 5 2", and end with a list with eleven numbers, like "5 6 1 1 0 9 1 8 7 8 6". In total, there are ten lists of numbers that the managers may recall.

E.1.2 Outcomes and Activities

- **Productivity Problems:** In the survey, managers were asked for productivity related problems that they have encountered in the last three months. These are the options: Equipment malfunctioning, shortage of inputs or inventory, errors made by employees, absenteeism, employees arriving late, unmotivated or shirking workers, unrealistic targets, and customer service complaints. We construct the index as an average of the managers' answers.

- **Active Operations:** Using different questions from the survey where, the managers answer about how often they assign tasks to the employees, do the equipment maintenance, supervise the cleaning of the area procedures, do product quality checks, and anticipate change in sales throughout the hours of operation. We construct the index as an average of the managers' answers.

- **Daily Operations:** To create this index, the manager's answers cover the activities that they include in their daily operations. These are the options: Store Design (relocation of furniture and decoration for special days), display placement, customer service, money handling, shoplifting prevention, premises maintenance, staff management, recruitment, and inventory-optimization.

E.1.3 Operations

- **Problem Solving:** In the survey, managers were asked for which strategies the follow or implement to problem-solving. These are the options: Observe and identify problems, draw priorities, decide how to solve each issue, communicate to everyone that should be involved in solving the issue, do everything on your own, address issues as they come, and ask employees to address issues as they come.

- **Id and Solution of Problems:** The survey aimed the managers to indicate the typical time frame between identifying a problem and resolving it. The options ranged from addressing the issue "Immediately" to resolving it "Within a day," "Up to a week," or taking "Longer than a week". Also, how the solutions that they implemented start to become a standard practice, managers could select from various methods, including incorporating the solutions into training manuals, putting up signs (when applicable) to guide actions when the issue arises, writing down the solution and sharing it with employees, or gathering all employees to inform them about the solution. Using the answers from these two questions, we create this index.

- **Manager Solves Problems:** After the questions where the managers mentioned the problems that they had faced during the last three months, the survey asked how they had identified those problems. We focused on the answer where the managers discovered problems while doing rounds across stations and solved these problems by themselves.

- **Problem Solving Employees Down:** For the problem-solving questions, the managers were asked to show the frequency in how they rely on their employees based on different topics: How often the employees identify and observe problems, how often the employees draw priorities, how often the employees decide how to solve an issue, how often the employees identify and observe problems, and how often the employees communicate to everyone that should be involved in solving the issue. Each of the previous question let the manager to answer in these different options: ”Never” ”Seldom,””Sometimes,””Frequently,” and ”often”. Then we construct the index as and average of the managers’ answers.

- **Problem Solving Upper Management:** For the problem-solving questions, the managers were asked to show the frequency in how they rely on their upper management based on different topics: How often the upper management identify and observe problems, how often the upper management draw priorities, and how often the upper management decide how to solve an issue. Each of the previous question let the manager to answer in these different options: ”Never” ”Seldom”, ”Sometimes”, ”Frequently”, and ”often”. Then we construct the index as an average of the managers’ answers.

- **Number of KPIs:** The survey asked managers to report the number of key performance indicators (KPIs) monitored in their establishment over the past year. These KPIs covered: units sold, cost of products, waste, quality satisfaction, inventory, absenteeism, and other controllable factors.

- **Freq KPI are Reviewed:** Related from the previous indicator, the survey asked how frequently key performance indicators (KPIs) were reviewed in their establishment over the past year. The options ranged from ”Yearly” and ”Quarterly” to more frequent reviews such as ”Monthly”, ”Weekly”, ”Daily” , and even ”Hourly or more frequently”. An additional option, ”Never”, was provided for establishments that did not review KPIs at all.

- **Freq Retrospective Learning:** In this variable, the survey captured the frequency with which managers conducted retrospective analyses in their stores. The survey asked how often they reflect on the following: What went right and how to ensure it happens again, what they can do differently next time, and what issues can be avoided from repeating in the future. For each of these questions, managers could select from a range of options, including ”Never,” ”Less than once a month,” ”Once a month,” ”Once a week,” ”Every other day,” and ”Every day.”Then we construct the index as and average of the managers’ answers.

- **Kaizen:** Analyzing the continuous improvement, the survey inquired about the incentives provided to workers for their contributions, offering options such as receiving a raise, being nominated for a promotion, public recognition for their contribution, or other forms of incentives.

- **Targets:** The survey asked managers about their strategies for ensuring that targets are met both in the short term and the long term. For short-term target achievement, managers could choose from various actions, such as doing rounds across stations to ensure order, talking to employees individually, providing positive reinforcement to high-performing employees, making low-performing employees aware of their work, demonstrating the correct way of working by example and switching workers around stations. For long-term target achievement, managers were asked about their approaches, including focusing on the quality of initial training, retraining workers who are falling behind on some tasks, and training high performers on a broader set of skills.

E.1.4 Human Resources Practices

- **Planning Employees:** The survey included a set of questions aimed at understanding the frequency of various workforce management practices. Managers were asked how often they engage in the following activities: Creating a list of employees available in case of an emergency, asking employees where they would like to be assigned, updating or reframing the detailed leave policy, and planning training for employees interested in specific tools or areas. For each question, managers could select from options indicating the frequency: ”Never,” ”Less than once a month,” ”Once a month,” ”Once a week,” ”Every other day,” or ”Every day.” Then we construct the index as an average of the managers’ answers.

- **Promote based on KPIs:** The survey asked managers to identify the criteria they consider when suggesting an employee for promotion. We focus on selected answers based on Productivity, and Compliance with objectives (KPIs).

- **Retaining the star performer:** For the highly productive workers, managers were asked the steps they would take to retain a star performer. The options included commending the worker on their effort, praising them in front of others, putting in a good word with superiors, recommending them for a promotion, assigning them to tasks they are interested in, or choosing to do nothing. Moreover, in the scenario where the highly productive worker expressed a desire to leave the company, managers were asked how they could act. The options included talking to the worker directly to convince them to stay, putting in a good word with superiors, recommending a salary increase, suggesting a promotion, or doing nothing.

- **Talk Underperformer Worker:** Using a question about how managers would handle a situation involving an under-performing worker. The scenario described a worker who may not be very motivated or may lack the right skills for the job. Respondents were asked to choose among several actions they might take to address this issue, including talking to the worker directly and in person, discussing the issue with the worker in the presence of other workers, trying to replace the worker, or doing nothing.

- **Freq Discuss KPIs Employees:** The survey asked the managers about the frequency with which managers discuss key performance indicators (KPIs) with their employees. Respondents were asked how often these discussions take place, with options ranging from ”More than once a day” to ”Less than once a month.” Additionally, the survey inquired about the most recent instance when KPIs were discussed with employees, offering choices such as ”Less than a week ago,” ”A week ago,” ”A month ago,” or ”More than a month ago.

- **Workers Discuss KPI:** The survey asked the managers who typically initiates discussions about key performance indicators efficiency and performance. Managers were given three options: ”I initiate the discussion,” ”The worker initiates the discussion,” or ”I, the employee, or the upper management initiate the discussion.”

- **Provide Feedback Employees:** The managers can select between the following options to show their approach to giving feedback to employees: Give comments as soon as possible, be accurate and describe the observed behavior and consequences, never give comments when angry, keep in mind the development of the employee, and ask the employee if he/she is willing to hear the comment.

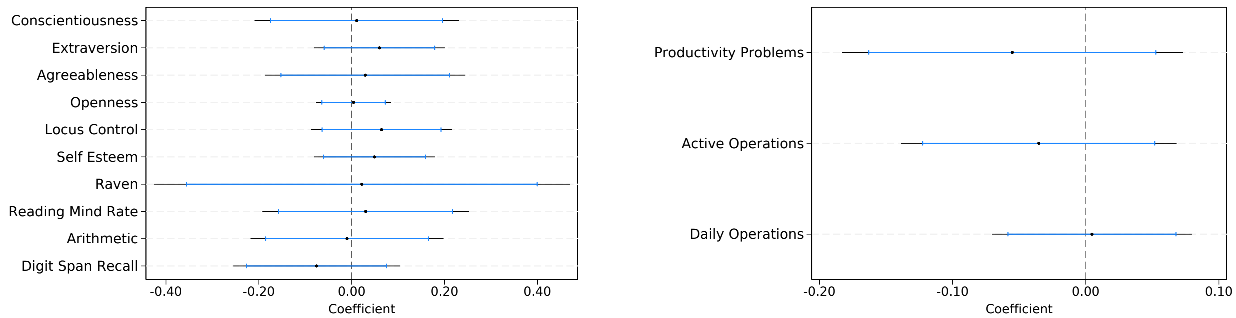
- **Freq Assess Employee Wellbeing:** The survey explored the frequency with which managers engage in key activities related to employee assessment and satisfaction. Using the following questions we create the index: How often they assess employees' strengths and opportunities for efficient task assignment, how often they investigate employees' motivation, and how often they identify ways to improve employee satisfaction. Managers could choose from options like ”Never,” ”Less than once a month,” ”Once a month,” ”Once a week,” ”Every other day,” or ”Every day.”

- **Freq Assess Employee Motivation:** The question, ”How often do you do the following retrospective analysis: What can I do to motivate my employees better?” aimed to assess how regularly managers reflect on and strategize ways to enhance employee motivation in their workplace. Managers could choose from options like ”Never,” ”Less than once a month,” ”Once a month,” ”Once a week,” ”Every other day,” or ”Every day.”

E.2 Multiple Hypothesis Testing: Survey Results Analysis

Figure E.1: Self-Reported Leadership Traits and Activities and Manager Fixed Effects

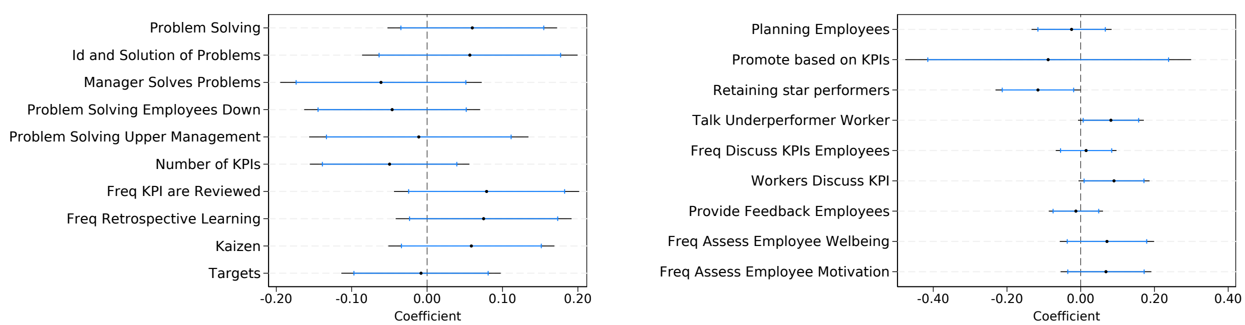
(a) Individual Characteristics (b) Outcomes and Activities



Notes: Figure E.1 plots the coefficients from regressing the manager fixed effects on each survey variable score, correcting for multiple hypothesis testing (Benjamini-Hochberg). The figure presents the coefficients from the main regression for individual characteristics as well as outcomes and activities for 204 managers from the quick service restaurant chain and 112 managers from the retail Company. The black lines represent 95% confidence interval, and the blue lines the 90% confidence interval.

Figure E.2: Self-Reported Adoption of Operational and HR Structured Management Practices and Manager Fixed Effects

(a) Operations (b) HR



Notes: Figure E.2 plots the coefficients from regressing the manager fixed effects on each survey variable, correcting for multiple hypothesis testing (Benjamini-Hochberg). The figure presents the coefficients from the main regression for operations and personnel practices for 204 managers from the quick service restaurant chain and 112 managers from the retail company. The black lines represent 95% confidence interval, and the blue lines the 90% confidence interval.

F Main Absenteeism Results in Table Format

Table F.1: Effect of Demand Shock and on Performance and Absenteeism, Car Company

	Log Total Cars Produced (1)	Absenteeism (2)	Absenteeism (LT vs HT) (3)
<8 weeks before the shock	0.068	-0.00672	
	(0.065)	(0.106)	
≤ 8 weeks after the shock	0.590	0.251**	0.514***
	(30.352)	(0.109)	(0.135)
>8 weeks after the shock	0.706*	0.360***	0.669***
	(0.355)	(0.0939)	(0.136)
≤ 8 weeks after the shock x HT			-0.542***
			(0.169)
>8 weeks after the shock x HT			-0.637***
			(0.184)
Observations	105	1,455	1,455
Avg. dep. var.	7.46	1.113	1.113
Lincom HT effect 8 weeks after			-0.027
Lincom HT effect >8 weeks after			0.032

Notes: Table F.1 reports the results for the estimation of equation 6 for the car company. Columns (1) and (2) present the estimates for the logarithm of the total number of cars produced and percentage change in absenteeism, respectively. In column (3), we interact relative time-to-treatment dummies with a dummy variable that is equal to 1 if the store was supervised by an HT manager before the shock. A High Training (HT) manager is defined as a manager whose estimated (training) fixed effect is above the median. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. *** p<0.01, ** p<0.05, * p<0.1.

Table F.2: Effect of Demand Shock on Performance and Absenteeism, Quick Service Restaurant Chain

	Log Transactions (1)	Log Transactions (LT vs HT) (2)	Absenteeism (3)	Absenteeism (LT vs HT) (4)
>8 weeks before Demand shock	0.035		-0.138	
	(0.027)		(0.104)	
≤ 8 weeks after the shock	0.110**	0.007	0.236	0.041
	(0.060)	(0.004)	(0.159)	(0.092)
>8 weeks after the shock	0.107***	0.004	0.269***	0.260**
	(0.041)	(0.002)	(0.103)	(0.098)
≤ 8 weeks after the shock x HT		0.002		0.040
		(0.004)		(0.149)
>8 weeks after the shock x HT		0.009**		-0.231*
		(0.003)		(0.119)
Observations	1,809	1,809	1,809	1,809
Avg. dep. var.	9.48	9.48	2.39	2.39
Lincom HT effect ≤ 8 weeks after		0.010***		0.081
Lincom HT effect >8 weeks after		0.014***		0.028

Notes: Table F.2 reports the results for the estimation of equation 6 for the quick service restaurant chain. Columns (1) and (3) present the estimates for log transactions and percentage change in absenteeism, respectively. In column (2) and (4), we interact relative time-to-treatment dummies with a dummy variable that is equal to 1 if the store was supervised by an HT manager before the shock and present the estimates for log transactions and percentage change in absenteeism, respectively. A High Training (HT) manager is defined as a manager whose estimated training fixed effect is above the median. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. *** p<0.01, ** p<0.05, * p<0.1.

Table F.3: Effect of Demand Shock and on Performance and Absenteeism, Retail Company

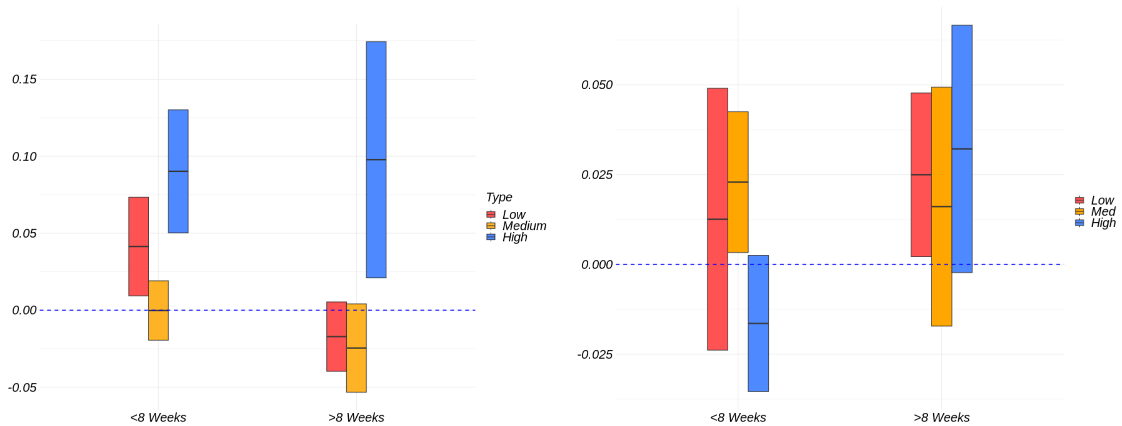
	Log Transactions	Log Transactions (LT vs HT)	Absenteeism	Absenteeism (LT vs HT)
	(1)	(2)	(3)	(4)
> 8 weeks before Demand shock	0.0210	-	-0.526	-
	(0.0160)		(0.420)	
$\leq$ 8 weeks after Demand shock	0.0201*	0.0127	0.685*	2.133***
	(0.0107)	(0.0215)	(0.368)	(0.679)
> 8 weeks after Demand shock	0.0402***	0.00940	0.407	0.713*
	(0.0134)	(0.0152)	(0.348)	(0.413)
$\leq$ 8 weeks after Demand shock x HT	-	-0.0169	-	-2.177***
		(0.0223)		(0.691)
> 8 weeks after Demand shock x HT	-	0.0319	-	0.0945
		(0.0232)		(0.580)
Observations	6,975	6,975	6,975	6,975
Avg. dep. var.	11.35	11.35	6.54	6.54
Lincom HT effect 8 weeks after	-	-0.004	-	-0.043
Lincom HT effect > 8 weeks after	-	0.041**	-	0.807*

Notes: Table F.3 reports the results for the estimation of equation 6 for the retail company. Columns (1) and (3) present the estimates for log transactions and percentage change in absenteeism, respectively. In column (2) and (4), we interact relative time-to-treatment dummies with a dummy variable that is equal to 1 if the store was supervised by an HT manager before the shock and present the estimates for log transactions and percentage change in absenteeism, respectively. A High Training (HT) manager is defined as a manager whose estimated training fixed effect is above the median. The estimation is at the unit-manager level. We include time and unit fixed effects. Standard errors are clustered at the unit level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

G Additional Robustness Checks on Absenteeism Results

G.1 Terciles Analysis

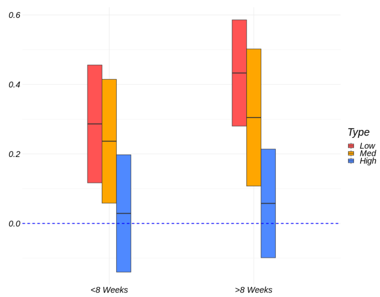
Figure G.1: Effect of Demand Shock on Log Transactions, by Manager Type (terciles)



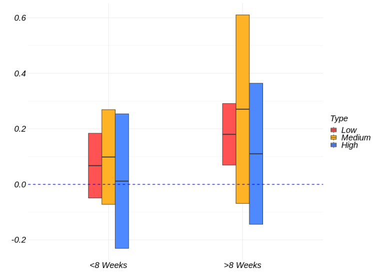
(a) Quick Service Restaurant Chain (b) Retail Company

Notes: Figure G.1 shows the impact of the shock on log transactions for the quick service restaurant chain and the retail company, eight weeks after the shock, and beyond eight weeks. We analyze the 83% interval confidence for three types of managers: Low training managers which are managers with training fixed effect below percentile 33, Medium training managers which are managers with training fixed effect below percentile 66 and above than percentile 33, and High training managers, which are the managers with training fixed effect above the 66th percentile. For the quick service restaurant chain, the effect of the shock for Low training manager in the first eight weeks is 4.7%; after eight weeks, it is -1.8%, the Medium training manager effect in the first eight weeks is 0%; after eight weeks, it is -2.7%, while the effect of the High training manager in the first eight weeks is 9%; after eight weeks, it is 9.8%***. Finally, for the retail company, the effect of the Low training manager in the first eight weeks is 1.26%; after eight weeks, it is 2.50%, the Mediumtraining manager effect in the first eight weeks is 2.29%; after eight weeks, it is 1.61%, while the effect of the High training manager in the first eight weeks is -1.64%; after eight weeks, it is 3.22%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between low-training, medium-training and high-training managers: *** p<0.01, ** p<0.05, * p<0.1.

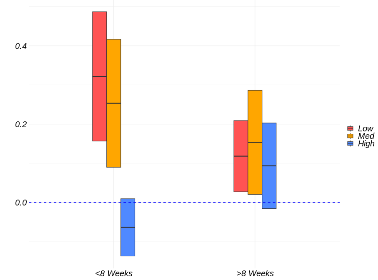
Figure G.2: Effect of Demand Shock on Absenteeism, by Manager Type (terciles)



(a) Car Manufacturer



(b) Quick Service Restaurant Chain

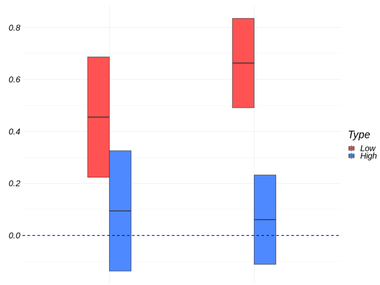


(c) Retail Company

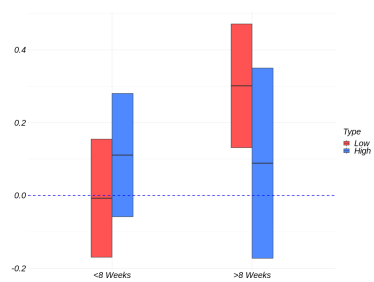
Notes: Figure G.2 shows the percentage change in absenteeism in a working group (car company), and in a store (quick service restaurant and retail companies), eight weeks after the shock, and beyond eight weeks. We analyze the 83% interval confidence for three types of managers: Low training managers which are managers with training fixed effect below percentile 33, Medium training managers with training fixed effects below the 66th percentile and above the 33th percentile , and high-training managers, which are the managers with training fixed effect above the 66th percentile. For the car company, the Low training manager effect in the first eight weeks is 28.65%; after eight weeks, it is 43.30%, the Medium training manager effect in the first eight weeks is 23.66%; after eight weeks, it is 30.49%, while the effect of the High training manager in the first eight weeks is 2.88%*; after eight weeks, it is 5.76%*. For the quick service restaurant chain, the effect of the Low training manager in the first eight weeks is 8%; after eight weeks, it is 18%, the Medium training manager effect in the first eight weeks is 10%; after eight weeks, it is 27%, while the effect of the High training manager in the first eight weeks is 2%; after eight weeks, it is 11%. Finally, for the retail company, the effect of the Low training manager in the first eight weeks is 32.19%; after eight weeks, it is 11.83%, the Medium training manager effect in the first eight weeks is 25.32%; after eight weeks, it is 15.33%, while the effect of the High training manager in the first eight weeks is -6.33%***; after eight weeks, it is 9.37%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between low-training, medium-training and high-training managers: *** p<0.01, ** p<0.05, * p<0.1.

G.2 Alternative Definitions of Absenteeism

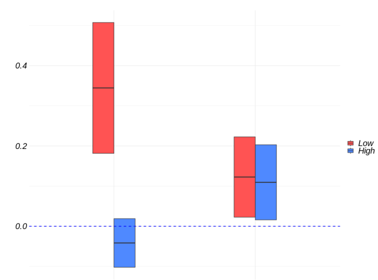
Figure G.3: Effect of Demand Shock on Total Absences, by Manager Type



(a) Car Manufacturer



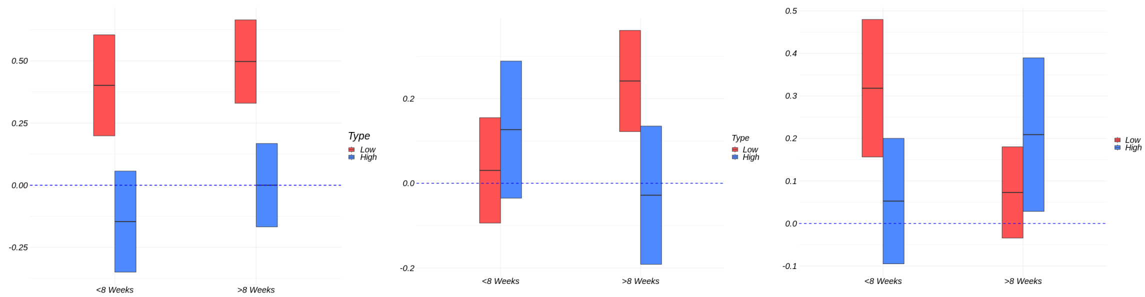
(b) Quick Service Restaurant Chain



(c) Retail Company

Notes: Figure G.3 shows the percentage change in total number of times employees are absent (total absences) in a working group (car company), and in a store (quick service restaurant and retail companies), both eight weeks after the shock, and beyond eight weeks. For the car company, the Low training manager effect in the first eight weeks is 45.53%; after eight weeks, it is 66.31%, while the effect of the High-training manager in the first eight weeks is 9.46%; after eight weeks, it is 6.08%**. For the quick service restaurant chain, the effect of the Low training manager in the first eight weeks is -0.7%; after eight weeks, it is 30.12%, while the effect of the High training manager in the first eight weeks is 11%; after eight weeks, it is 8.87%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is 31.80%; after eight weeks, it is 12.30%, while the effect of the High-training manager in the first eight weeks is -5.26%**; after eight weeks, it is 10.96%. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure G.4: Effect of Demand Shock on Share of Absent Employees, by Manager Type



(a) Car Manufacturer

(b) Quick Service Restaurant Chain

(c) Retail Company

Notes: Figure G.4 shows the percentage change in the share absent employees in a working group (car company), and in a store (quick service restaurant and retail companies), both eight weeks after the shock, and beyond eight weeks. For the car company, the Low-training manager effect in the first eight weeks is 40.18%; after eight weeks, it is 49.74%, while the effect of the High-training manager in the first eight weeks is -14.65%**; after eight weeks, it is 0%**. For the quick service restaurant chain, the effect of the Low-training manager in the first eight weeks is 3.05%; after eight weeks, it is 24.16%, while the effect of the High-training manager in the first eight weeks is 12.6%; after eight weeks, it is -2.81%**. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is 34.46%; after eight weeks, it is 12.28%, while the effect of the High-training manager in the first eight weeks is -4.14%*; after eight weeks, it is 10.96%. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

H Heterogeneity Within and Across Teams

In this section we study whether the effects of HT managers on absenteeism are heterogeneous both within and across stores. First, we examine whether the impact of HT managers varies for different employees according to their previous training experience, organizational level (low, middle, and high-ranking workers) and occupation (looking separately at occupations that were differentially exposed to the demand shock). Second, we investigate the differential effects of HT managers across stores, focusing in particular on the heterogeneity across stores in which employees have better outside options during the demand shock.

H.1 Heterogeneity within Teams

Hierarchical Layers For the three firms, we observe a rich organizational structure with several hierarchical “ranks” within stores. We leverage this structure to group workers into three categories: low, medium, and high-ranked workers. The low-ranked worker category includes all entry-level workers or those in the lowest positions within the organizational chart. The medium-ranked category comprises more experienced workers with higher responsibilities who may oversee specific departments or functions within the organization. Finally, the high-ranked worker category consists of senior positions, including workers managing a section or department within the unit of analysis.

We begin our analysis by examining the effects of the demand shock on absenteeism for different levels of the organizational hierarchy. Specifically, we run our main specification, equation

(6), for three dependent variables: total absenteeism for low-ranked workers, total absenteeism for medium-ranked workers, and total absenteeism for managers or high-ranked workers.[58]

Our findings indicate that the effects of the shock on absenteeism are more pronounced at lower levels of the firm hierarchy. Figure H.1 shows that low-ranked workers exhibit the highest percentage change in absenteeism, followed by medium-ranked workers and then managers or high-ranked workers. For the car company, low-ranked workers show an increase of around 20% in absenteeism, while high-rank workers only experience close to a 2% increase after the shock.

To analyze the effect of HT managers on different hierarchical layers, we estimate equation (6) interacting the relative time-to-treatment dummies with the HT dummy variable and plot the results for each of the subgroups. Figure H.2 shows that HT managers matter the most for low-rank worker absenteeism. We see that the differential between high and low managers on absenteeism is larger when we restrict our analysis to low-rank workers. [59]

Occupations In this section, we test the relevance of HT managers across different occupations inside the unit/store. This analysis is motivated by the fact that we expect different occupations were more exposed to the demand shock than others. In the car company, the trim sector (which requires attention to detail and is the most skill-intensive stage of production), was likely to be the hardest to operate under pressure.[60] Therefore, compared to other less detail-intensive sectors, workers in the trim sector are likely to have experienced the highest increase in workload after the new targets were announced relative to other production stages, such as the chassis sector. Similarly, for the quick service restaurant chain, the introduction of the delivery service app significantly increased the workload for apprentices, younger and less experienced workers who typically handle simple but labor-intensive and repetitive tasks. As the number of transactions and items demanded rose, apprentices were likely to have faced a greater increase in workload relative to other occupations (such as cleaning service, kitchen, customer service, and lobby service). Finally, for the retail company, the introduction of the delivery app significantly affected cashiers, who directly interact with the delivery staff and often help fulfill orders.

Figure H.3 shows that after the shock, sectors with higher exposure experience higher levels of absenteeism. This is especially true for the three identified sectors in each company: trim in the car company, apprentices in the quick service restaurant chain, and cashiers in the retail company. We observe a direct and positive relationship between exposure to the shock and absenteeism.[61] Figure H.4 shows that the impact of HT managers is particularly significant in these high-exposure

[58] For the car company, we only have two layers in the teams, low ranked workers and managers.

[59] Appendix Figure G.4 repeats the same exercise using the share of absent employees, showing similar results.

[60] Recall that the trim sector has the highest number of defects per vehicle pre-shock.

[61] For the car company, we see a higher impact on absenteeism in the trim sector in the immediate 8 weeks after the shock and after 8 weeks, but it is not statistically significantly different from the chassis sector.

occupations. Specifically, HT managers effectively mitigate the effect of the shock in these high-exposure sectors.

Overall, the figures suggest that HT managers play a crucial role in mitigating the effects of demand shocks on absenteeism in high-exposure occupations. This highlights the importance of targeted managerial training in sectors most vulnerable to increased workload and pressure.

H.2 Heterogeneity across Teams

Employees' response to increases in workload are also shaped by their outside options, which, in turn are largely determined by local labor markets. Specifically, it is likely that the salience of the demand shock was higher in areas where there are stronger outside employment options relative to weaker labor markets. We proxy for outside options using the unemployment rate in the state where stores are located two weeks before the shock.[62] First, we divide all our stores at into two groups: high and low unemployment areas (relative to the national median). Then, we test the impact of the shock on these two subgroups using our staggered event study design (our main specification, equation 6), incorporating a dummy variable that differentiates these subgroups.[63] We plot the results of the event study design for the two groups in Figure H.5.

We observe that the rise in absenteeism after the demand shock is more pronounced in areas with low unemployment for both the quick service restaurant chain and retail company. Specifically, in both companies, absenteeism increases significantly in the immediate eight weeks after the shock and in the subsequent period in states with low unemployment rates. Conversely, in areas with high unemployment rates, there is little to no change in absenteeism.

Following this initial evidence, we estimate the effect of HT and LT managers in states with low unemployment rates (i.e. where outside options are more likely to exist for workers) using our main equation (6) and include our usual indicator variable for HT and LT managers. Figure H.6 shows that HT managers experience a lower increase in absenteeism compared to LT managers in low-unemployment states.

[62] For the car company, we only have one location and several working groups; thus, this exercise is not feasible.

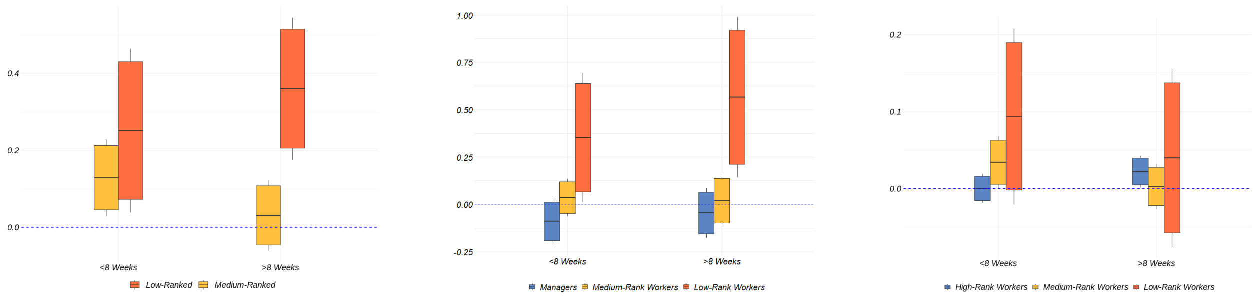
[63] These groups (i.e., high and low unemployment rates) are the same for the quick service restaurant chain and the retail company

Figure H.1: Effect of the Demand Shock on Absenteeism, by Hierarchical Level

(a) Car Manufacturer

(b) Quick Service Restaurant Chain

(c) Retail Company



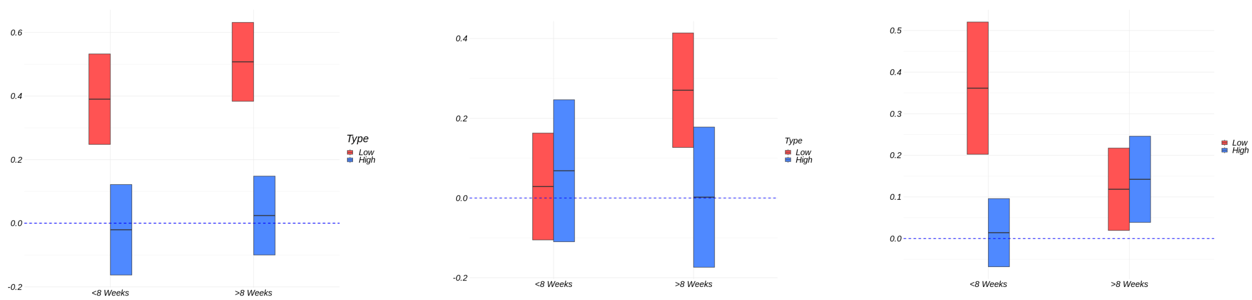
Notes: Figure H.1 shows the percentage change in absent employees by hierarchical level for each company. We analyze Low- and Medium-rank employees for the car company, Low-rank employees, Medium-rank employees, and Managers for the quick service restaurant chain and retail company. For the car manufacturer, the effect for the Low-rank employees in the first eight weeks is 25.12%; after eight weeks, it is 36%. The effect for the Managers in the first eight weeks is 12.89%; after eight weeks, it is 3.10%. For the quick service restaurant chain, the effect for the Low-rank employees in the first eight weeks is 35.3%; after eight weeks, it is 56.6%. The effect for the Medium-rank employees in the first eight weeks is 3.57%; after eight weeks, it is 1.92%. Finally, for the Managers the effect in the first eight weeks is -8.9%; after eight weeks, it is -4.6%. For the retail company, the effect for the Low-rank employees in the first eight weeks is 9.39%; after eight weeks, it is 4.00%. The effect for the Medium-rank employees in the first eight weeks is 3.41%; after eight weeks, it is 0.27%. For the Managers the effect in the first eight weeks is 0.00%; after eight weeks, it is 2.21%. We compare the coefficients of the types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level.

Figure H.2: Effect of the Demand Shock on Absenteeism, by Manager Type (High and Low Training) for Lower Hierarchical Levels

(a) Car Manufacturer

(b) Quick Service Restaurant Chain

(c) Retail Company



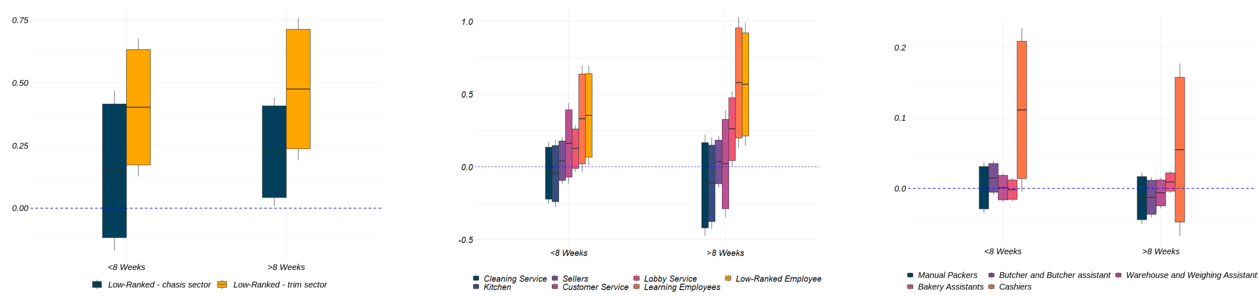
Notes: Figure H.2 shows the percentage change in absenteeism for the Low-ranked employees for each company. We show the effect, both eight weeks after the shock and beyond eight weeks. For the car manufacturer, the effect of the Low-training manager in the first eight weeks is 39.02%; after eight weeks, it is 50.75%. The effect of the High-training manager in the first eight weeks is -2.05%**; after eight weeks, it is 2.43%**. For the quick service restaurant chain, the effect of the Low-training manager in the first eight weeks is 3%; after eight weeks, it is 27%. The effect of the High-training manager in the first eight weeks is 7%*; after eight weeks, it is 0%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is 33.17%; after eight weeks, it is 11.18%, while the effect of the High-training manager in the first eight weeks is 0.89%**; after eight weeks, it is 12.72%. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure H.3: Effect of the Demand Shock on Absenteeism, by Occupation

(a) Car Manufacturer

(b) Quick Service Restaurant Chain

(c) Retail Company



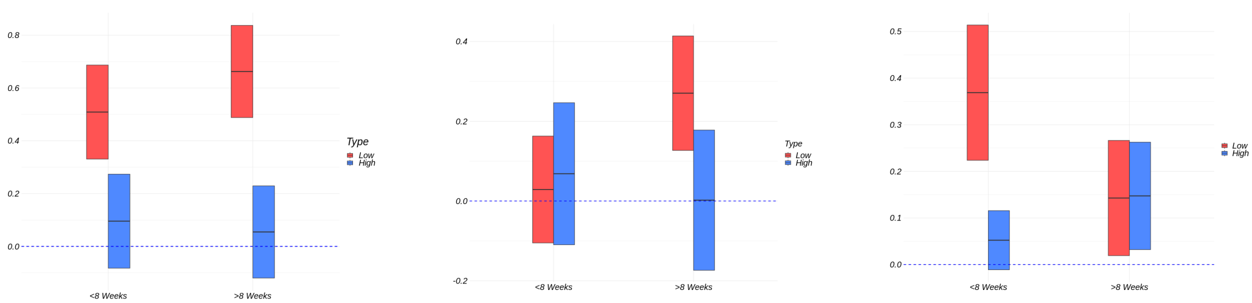
Notes: Figure H.3 shows the percentage change in absent employees by occupation for the Low-ranked employees on each company. We analyze the chassis and trim sectors for the car company; for the quick service restaurant chain, we analyze employees in cleaning, lobby and customer service, kitchen, sellers and apprentices; finally, for the retail company, we analyze the employees that are in manual packers, butcher and butcher assistants, bakery assistants, warehouse, and cashiers. For the car manufacturer, the effect for the chassis sector employees in the first eight weeks is 14.91%; after eight weeks, it is 22.53%, while the impact for the trim sector in the first eight weeks is 40.30%; after eight weeks, it is 47.58%.
For the quick service restaurant chain, the effect on the cleaning service employees in the first eight weeks is -4.3%, after eight weeks, it is -12.7%. The effect for the sellers in the first eight weeks is 4.17%, after eight weeks, it is 3.47%. The effect for the lobby service employees in the first eight weeks is 12.6%, after eight weeks, it is 26%. The effect for the kitchen employees in the first eight weeks is -4.57%, after eight weeks, it is -11.3%. The effect for the customer service employees in the first eight weeks is 16.1%, after eight weeks, it is 2%. The effect for the apprentices in the first eight weeks is 32.9%, after eight weeks, it is 57.7%. Finally, the effect for the low-rank employees in general in the first eight weeks is 35.3%, after eight weeks, it is 56.6%.
For the retail company, the effect for the manual packers in the first eight weeks is -0.09%, after eight weeks, it is -1.32%; the effect for the butchers and butcher assistants in the first eight weeks is 1.40%, after eight weeks, it is -1.10%; the effect for the warehouse and weighing assistants in the first eight weeks is 0.15%, after eight weeks, it is -0.65%; the effect for the bakery assistants employees in the first eight weeks is -0.21%, after eight weeks, it is 0.91%; finally, the effect for the cashiers in the first eight weeks is 8.31%**, after eight weeks, it is 4.89%. We compare the coefficients of all types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level.

Figure H.4: Effect of the Demand Shock on Absenteeism, by Manager Type (High and Low Training) for Occupations More Exposed to the Shock

(a) Car Manufacturer: Trim

(b) Quick Service Restaurant: Apprentices

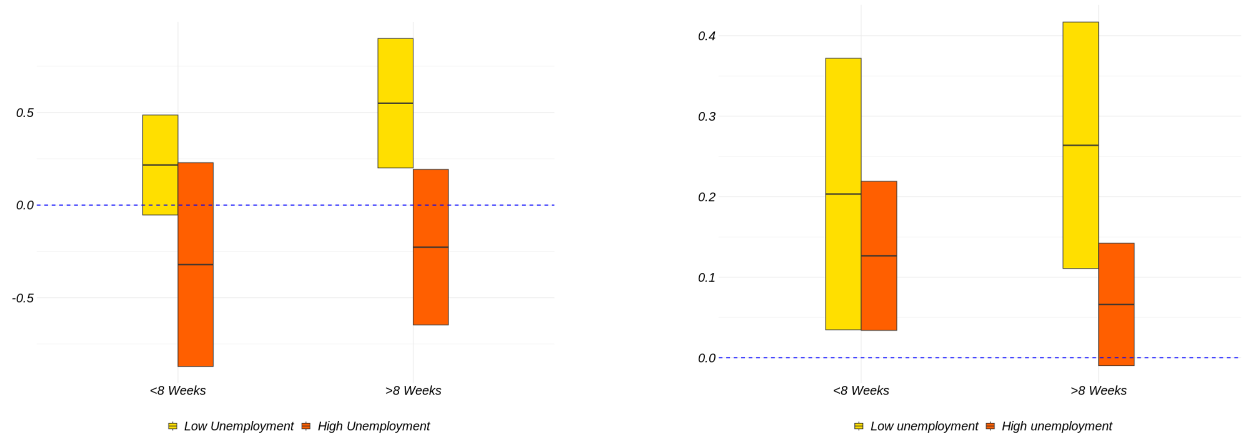
(c) Retail Company: Cashiers



Notes: Figure H.4 shows the percentage change in absenteeism forsectors more exposed to the shock: trim for the car company, apprentices for the quick service restaurant chain, and cashier employees for the retail company. The analysis is done eight weeks after the shock, and the effect after more than eight weeks. For the sector trim employees, the effect of the Low-training manager in the first eight weeks is 50.89%; after eight weeks, it is 66.26%, while the effect of the High-training manager in the first eight weeks is 9.57%**; after eight weeks, it is 5.48%**. For the apprentices, the effect of the Low-training manager in the first eight weeks is 2.88%; after eight weeks, it is 27.04%, while the effect of the High-training manager in the first eight weeks is 6.83%; after eight weeks, it is 0.02%*. Finally, for the cashiers, the effect of the Low-training manager in the first eight weeks is 34%; after eight weeks, it is 14%, while the effect of the High-training manager in the first eight weeks is 4.7%**; after eight weeks, it is 13%. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure H.5: The Effect of the Demand Shock in Low and High Unemployment States

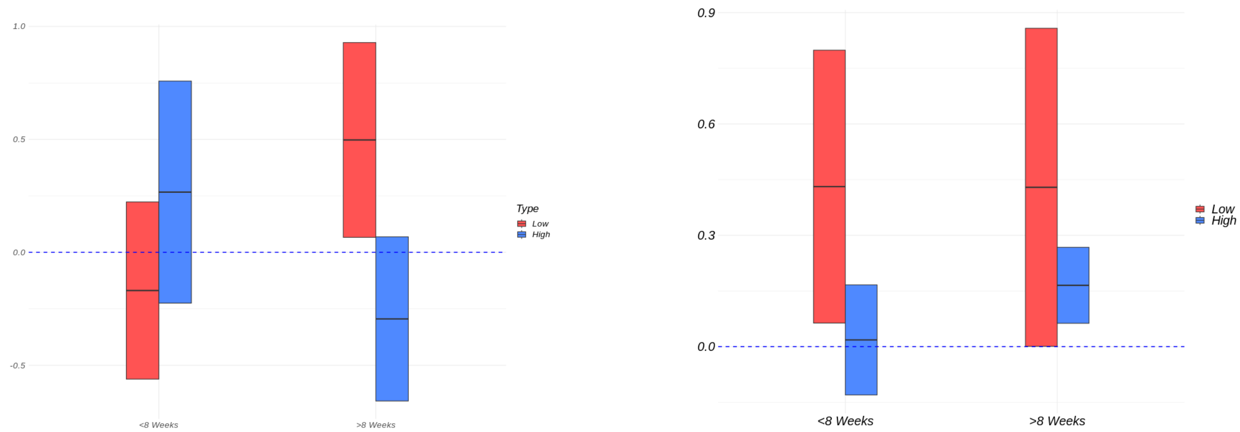
(a) Quick Service Restaurant Chain (b) Retail Company



Notes: Figure H.5 shows the percentage change in absenteeism in Low and High-unemployment areas (as a proxy for the competitiveness of the labor market) for the quick service restaurant chain and retail company, both eight weeks after the shock and beyond eight weeks. We classify areas by comparing their unemployment rates to the national median, designating areas with above-median unemployment as High unemployment and those below the median as low unemployment. For the quick service restaurant chain, the effect of the shock in Low unemployment areas in the first eight weeks is 21.64%; after eight weeks, it is 55%, while the effect in the High unemployment in the first eight weeks is -32.08%; after eight weeks, it is -22.68%**. For the retail company, the effect of the shock in Low unemployment areas in the first eight weeks is 20.32 %; after eight weeks, it is 26.38%, while the effect in the high unemployment in the first eight weeks is 12.65 %; after eight weeks, it is 6.61%*. We compare the coefficients of both types of employment areas at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between High unemployment and Low unemployment areas: *** p<0.01, ** p<0.05, * p<0.1.

Figure H.6: The Effect of the Demand Shock by Manager Type (High and Low Training) in Low Unemployment States

(a) Quick Service Restaurant Chain (b) Retail Company



Notes: Figure H.6 shows the percentage change in absenteeism in Low-unemployment areas for stores managed by HT and LT managers eight weeks after the shock, and more than eight weeks after the shock. For the quick service restaurant chain, the effect of the shock for Low-training managers in the first eight weeks is -21.64%; after eight weeks, it is 50%, while the effect for the High-training management in the first eight weeks is 26%; after eight weeks, it is -28%**. For the retail company, the effect of the shock for Low-training managers in the first eight weeks is 43.12%; after eight weeks, it is 42.94%, while the effect for the High-training managers in the first eight weeks is 1.82%; after eight weeks, it is 16.53%. We compare the coefficients of both types of managers with a 83% confidence interval. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

I Another Shock: Extreme Rainfall

Following Bandiera et al. (2018), we study the response to a different type of "shock" that requires workers to exert more uncompensated effort: extreme rainfall. Extreme rainfall significantly increases the effort required for employees to attend work by increasing traffic congestion.

We impute rainfall in millimeters using data from the nearest weather towers to each city within a 50 km radius.[64] Using this daily rainfall data, we define an extreme rainfall event as one where the rainfall for the city in a bi-week is higher than the mean annual rainfall for the city.[65] We analyze a panel of shocks at the store level using a time window of two biweekly periods before and after the shock.

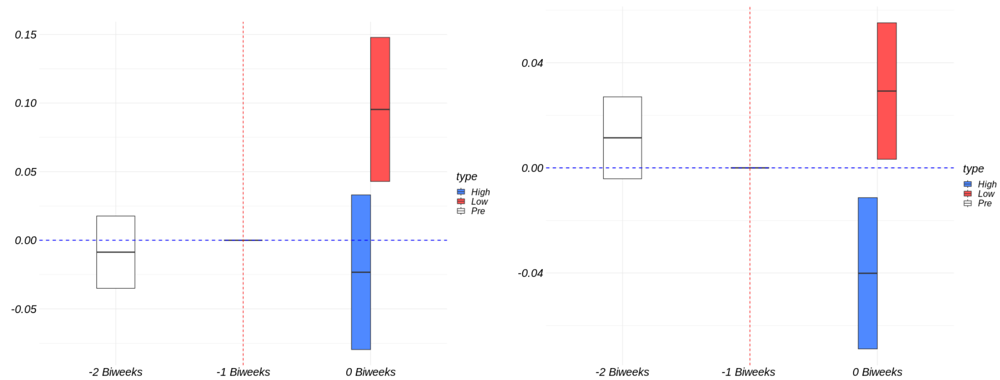
Results from this estimation are shown in Figure I.1, where we plot the percentage change in absenteeism in a store after a rainfall shock eight weeks after the shock and beyond for the quick service restaurant chain and retail company. As expected, we find no pretrends in absenteeism's response to rainfall. We find that an extreme rainfall shock increases absenteeism among LT managers but not HT managers. An extreme rainfall event increases absenteeism for LT managers

[64] We use weather information from Colombia's Institute of Hydrology, Meteorology and Environmental Studies (IDEAM). As we mentioned before, The data contains daily measures of rainfall and temperature from 303 measurement stations. We assign weather variables to municipalities using inverse-distance weighting.

[65] We exclude the car company from this exercise, given that all working groups are located in the same assembly unit, resulting in no geographical variation.

by 9.8% in the quick service restaurant chain on average, while it does not affect absenteeism for units under HT training management. For the retail company, a rainfall event increases absenteeism for LT managers by 3.33%, but it does not change absenteeism for HT managers on average.

Figure I.1: Effect on Rainfall Shock on Absenteeism by Manager Type (High and Low Training)



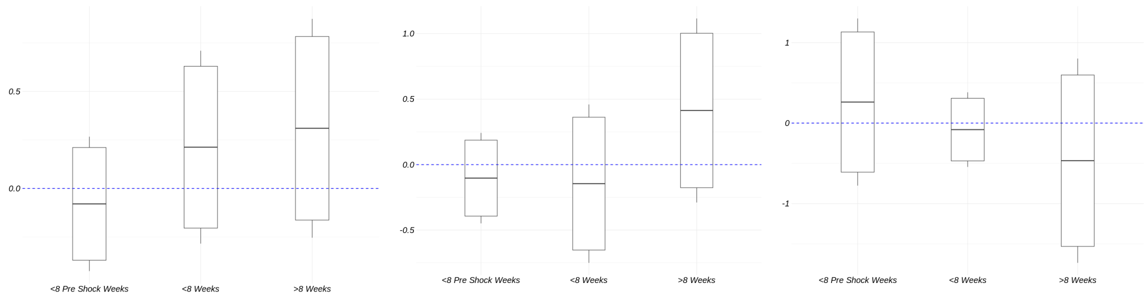
(a) Quick Service Restaurant Chain (b) Retail Company

Notes: Figure I.1 shows the percentage change in absenteeism in a store for the quick service restaurant chain and retail company two weeks after the rainfall shock. For the quick service restaurant chain, the effect of the Low-training managers in the two weeks is 9.8%, while the effect of the HT manager in the two weeks is -2.5%**. Finally, for the retail company, the effect of the LT manager in the two weeks is 2.9%, while the effect of the HTmanager in the two weeks is -4.0%**. We compare the coefficients of both types of managers at an interval confidence of 83%. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

J Why do High Training Managers Affect Absenteeism during a Demand Shock?

J.1 Differences by Employees' Training Status

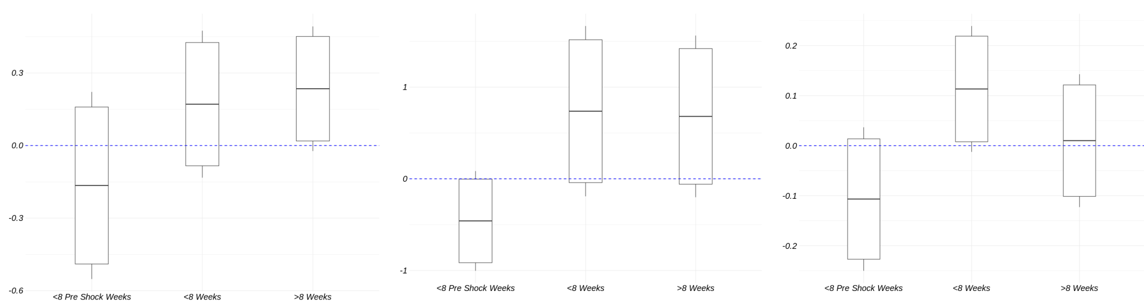
Figure J.1: Effect of Demand Shock on Absenteeism for High-Training Employees under a High Training manager



(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company

Notes: Figure J.1 shows the impact of having a High-training manager during a shock on the percentage change in absenteeism for High training employees at a unit level, both eight weeks after the shock, and beyond eight weeks. For the car company, effect in the first eight weeks is 21.29%; after eight weeks, it is 31.01%. For the quick service restaurant chain, the effect in the first eight weeks is -15%; after eight weeks, it is 48%. Finally, for the retail company, the effect in the first eight weeks is -10%; after eight weeks, it is 47%. The bars in the graph represent the 90% confidence intervals, while the lines indicate the 95% confidence intervals. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. *** p<0.01, ** p<0.05, * p<0.1.

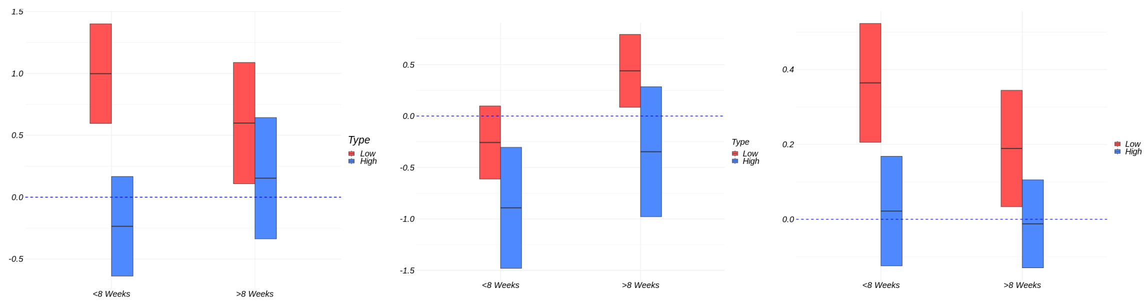
Figure J.2: Effect of Demand Shock on Absenteeism for Low-Training Employees



(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company

Notes: Figure J.2 shows the HT effect on the percentage change in absenteeism for low training employees before the shock, in a working group (car company), and in a store (quick service restaurant and retail companies), eight weeks after the shock, and the effect after more than eight weeks. For the car company, effect in the first eight weeks is 17.13%; after eight weeks, it is 23.52%. For the quick service restaurant chain, the effect in the first eight weeks is 75%; after eight weeks, it is 70%. Finally, for the retail company, the effect in the first eight weeks is 12%; after eight weeks, it is 1%. The bars in the graph represent the 90% confidence intervals, while the lines indicate the 95% confidence intervals. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. *** p<0.01, ** p<0.05, * p<0.1.

Figure J.3: Effect on Absenteeism for Low-Training Employees, by Manager type

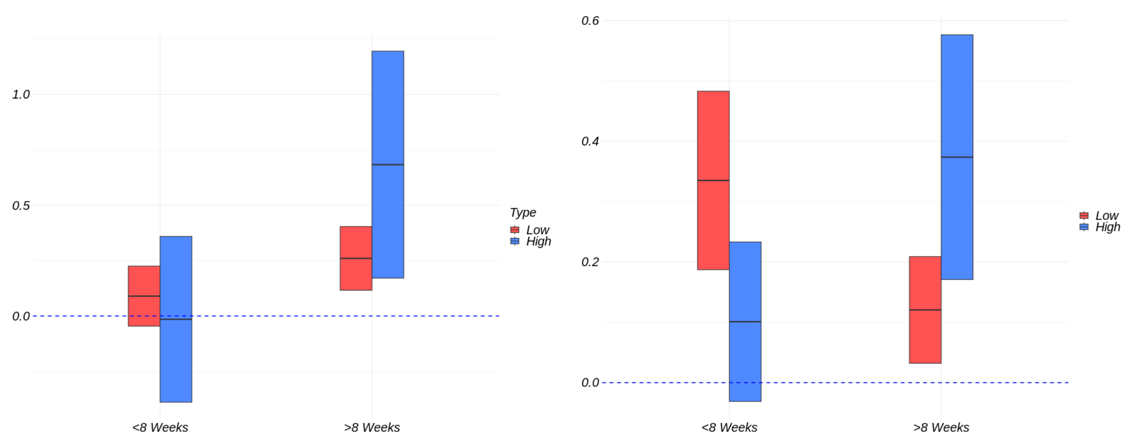


(a) Car Manufacturer (b) Quick Service Restaurant Chain (c) Retail Company

Notes: Figure J.3 shows the HT effect on the percentage change in absenteeism for low training employees before the shock, in a working group (car company), and in a store (quick service restaurant and retail companies), eight weeks after the shock, and the effect after more than eight weeks. For the car company, the Low-training manager effect in the first eight weeks is 99.74%; after eight weeks, it is 59.79%, while the effect of the High-training manager in the first eight weeks is -23.78%**; after eight weeks, it is 15.31%. For the quick service restaurant chain, the effect of the Low-training manager in the first eight weeks is -26%; after eight weeks, it is 48%, while the effect of the High-training manager in the first eight weeks is -85%; after eight weeks, it is -30%*. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is 37%; after eight weeks, it is 19%, while the effect of the High-training manager in the first eight weeks is 5%**; after eight weeks, it is -2%. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

J.2 Differences by Employees' Exposure to HT Managers

Figure J.4: Effect of the Demand Shock on Absenteeism, by Manager Type *High and Low Training : Subsample of Stores where the Manager Left After the Shock



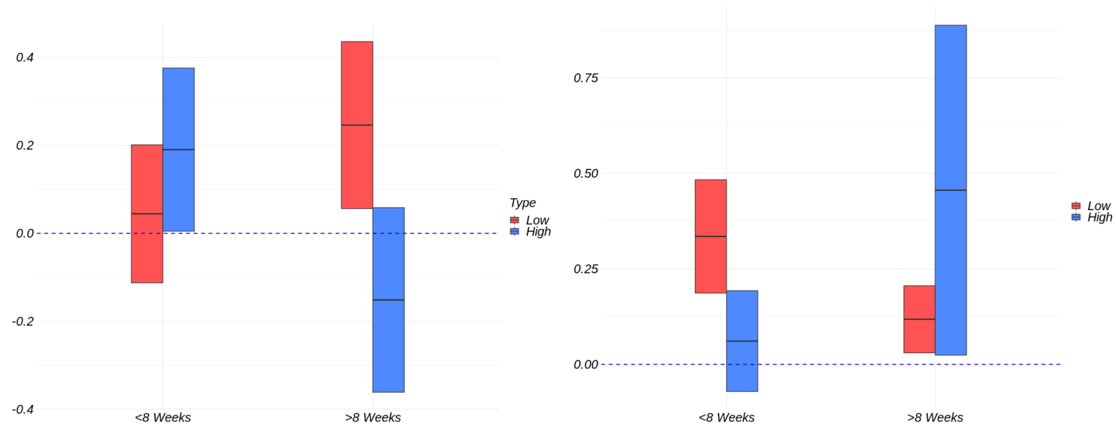
(a) Quick Service Restaurant Chain (b) Retail Company

Notes: Figure J.4 shows the percentage change in absenteeism at the unit level where the High-type manager leaves after the shock. For the quick service restaurant chain, the effect of the Low-training manager in the first eight weeks is a 15% increase, and 25% increase after eight weeks, while the effect of the High-training manager starts with a -3% decrease in the first eight weeks, growing to 67% after eight weeks. In the retail company, the Low-training manager's effect on absenteeism is a 33% increase within the first eight weeks, which then decreases to a 12% increase after eight weeks. Meanwhile, the high-training manager initially increases absenteeism by 10%*, but this effect increase into a 38% after eight weeks. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

Figure J.5: Effect of Demand Shock on Absenteeism, by Manager Type (High and Low Training), for Newly Appointed Managers

(a) Quick Service Restaurant Chain

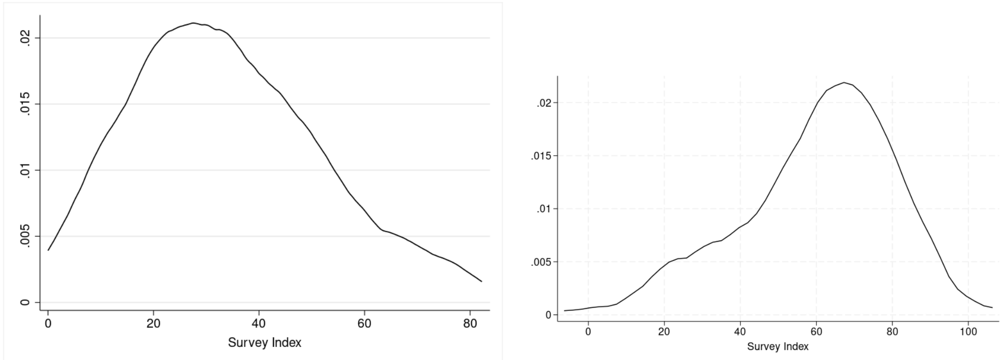
(b) Retail Company



Notes: Figure J.5 shows the percentage change in absenteeism in a store for the quick service restaurant chain and retail company, both eight weeks after the shock and after eight weeks. The sample includes only stores that transitioned from an LT to an HT manager before the demand shock occurred. For the quick service-restaurant chain, the effect of the LT manager in the first eight weeks is 4.35%; after eight weeks, it is 25.32%. The effect of the HT manager in the first eight weeks is 19.61%; after eight weeks, it is -15.3%**. Finally, for the retail company, the effect of the LT manager in the first eight weeks is 34.5%; after eight weeks, it is 11.82%, while the effect of the HT manager in the first eight weeks is 6.1%**; after eight weeks, it is 45.6%. We compare the coefficients of both types of managers at an interval confidence of 83%. The estimation is at the unit-manager level. Standard errors are clustered at the unit level. Asterisks (*) are used to denote statistically significant differences between HT and LT managers: *** p<0.01, ** p<0.05, * p<0.1.

J.3 Participatory Practices Index

Figure J.6: Survey Index Distribution



(a) Quick Service Restaurant Chain (b) Retail Company

Notes: Figure J.6, panel (a) and (b) show the distribution of the participatory index for the quick service restaurant and retail company, respectively. The index is constructed by running a principal component analysis and selecting the most important component from these variables: Extraversion, Agreeableness, Reading Mind Rate, Talk Underperformer Workers, and Discussing KPIs with the workers. The values are standardized between 0 and 100, subtracting the minimum value and dividing by the range (maximum minus minimum), then multiplying the result by 100.

J.4 Manager FE's and Participatory Practice Index Analysis

Table J.1: HT Manager vs Participatory Practice Index (PPI), Quick Service Restaurant Chain

VARIABLES	(1) Absenteeism	(2) Absenteeism	(3) Absenteeism
Demand Shock	0.351	0.00859	0.249
	(0.393)	(0.400)	(0.401)
Demand Shock x HT Manager	-0.813**		-1.044**
	(0.365)		(0.391)
Demand Shock x High-PPI Manager		0.244	0.650
		(0.490)	(0.437)
Constant	3.409***	3.396***	3.400***
	(0.187)	(0.183)	(0.184)
Observations	1,131	1,131	1,131
Lincom HT Manager	-0.463		-0.796
Lincom High-PPI Manager		0.252	.0.899
Avg. dep. var.	3.432	3.432	3.432
Stores	52	52	52
Treated Stores	22	22	22

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table J.1 reports the results for the estimation of equation 6 for the quick service restaurant chain, replacing the full set of time-to-treatment indicators with a simple post-treatment dummy. Column (1) repeat the results presented in Table F.2, for the sample of managers that match with the survey (204 managers). Column (2) replaces the HT dummy variable with a dummy variable that is equal to 1 for managers whose participatory index (PPI) is above the median. The PPI index is constructed by running a principal component analysis and selecting the most important component from these variables: Extraversion, Agreeableness, Reading Mind Rate, Talk Underperformer Workers, and Discussing KPIs with the workers. Column (3) includes both HT and high-PPI manager dummy. We include time and unit fixed effects. Standard errors are clustered at the unit level. The significance level is represented as: *** p<0.01, ** p<0.05, * p<0.1.

Table J.2: HT Managers vs Participatory Practice Index (PPI), Retail Company

VARIABLES	(1) Absenteeism	(2) Absenteeism	(3) Absenteeism
Demand Shock	0.815**	0.721**	0.807**
	(0.336)	(0.332)	(0.337)
Demand Shock x HT Manager	-1.109*		-1.279**
	(0.613)		(0.628)
Demand Shock x High-PPI Manager		-0.129	0.715
		(0.355)	(0.462)
Observations	4,354	4,354	4,354
Lincom HT Manager	-0.294	-	-0.472
Lincom High-PPI Manager	-	0.591	1.522 ***
Avg. dep. var.	6.75	6.75	6.75
Stores	52	52	52
Treated Stores	41	41	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table J.2 reports the results for the estimation of equation 6 for the retail company, replacing the full set of time-to-treatment indicators with a simple post-treatment dummy. Column (1) repeat the results presented in Table F.3, for the sample of managers that match with the survey (112 managers). Column (2) replaces the HT dummy variable with a dummy variable that is equal to 1 for managers whose participatory index (PPI) is above the median. The PPI index is constructed by running a principal component analysis and selecting the most important component from these variables: Extraversion, Agreeableness, Reading Mind Rate, Talk Underperformer Workers, and Discussing KPIs with the workers. Column (3) includes both HT and high-PPI manager dummy. We include time and unit fixed effects. Standard errors are clustered at the unit level. The significance level is represented as: *** p<0.01, ** p<0.05, * p<0.1.

K Model

K.1 Basic Set Up

Production We model a firm as consisting of a continuum of organizational units, $\mathscr{M}$, representing teams or stores. Each unit employs a group of homogeneous workers supervised by a manager, $m \in \mathscr{M}$. Within each unit, the production process involves workers performing easy (E) and difficult (D) tasks. Workers are initially assigned to easy jobs (that is, jobs that only include easy tasks), but the firm commits to promoting them to difficult jobs (that is, jobs that include at least one difficult tasks) if they acquire firm-specific skills through training at a cost $c \geq 0$.[66] This investment is firm-specific and thus does not affect their outside options.

The output *per unit of time* for a unit (store or team) with type s workers is given by:[67]

$$y(s) = \alpha y_D(s) + (1-\alpha) y_E(s), \tag{7}$$

where $\alpha \in [0,1]$ denotes the fraction of difficult tasks needed in production, with the remaining $1-\alpha$ fraction being easy tasks, $s = 1$ refers to workers who invest in training, $s = 0$ refers to those who do not, and the indicator functions y_D and y_E satisfy the following inequality:

$$0 = y_D(0) < y_E(0) < y_E(1) < y_D(1). \tag{8}$$

Inequality (8) implies that *i*) training improves the productivity of both tasks; and *ii*) a trained worker is effectively assigned to a difficult task.

Training Like in Prendergast (1993), to encourage investment in training, the firm commits to a differentiated wage structure. Specifically, the firm sets a higher wage, w_D, for the difficult job and a lower wage, $w_E \leq w_D$, for the easy job. Like the organizations in our study, the firm communicates that trained workers will be promoted to the higher-paying D job. Unlike Prendergast (1993), however, the actual probability of a promotion conditional on training is perceived by the workers to depend on middle managers.[68] Consequently, a worker's decision to invest in training depends not only on the wage premium associated with the promotion to a difficult job ($w_D - w_E$) but also on their manager's type. This variation is captured by a continuous random variable, X, which takes

[66] In this section, we assume that workers who invest in training will be promoted in the same period. In section K.3, we explore firm dynamics when the training decision and the promotion and wage increase happen in the subsequent period.

[67] In subsequent sections, we present the worker's optimization problem, where we compute the optimal number of working hours.

[68] For example, managers may vary in their effectiveness in communicating the benefits of training to workers, and/or their willingness to support workers' candidacy for promotion.

values between 0 and 1. High X managers have no influence on the wage increase associated with a D job, but they can convey a higher probability of being promoted after training occurs. A worker paired with manager m (whose type is denoted by X_m) decides to invest in training if the following condition holds:

$$X_m \cdot w_D + (1 - X_m) \cdot w_E - w_E = X_m \cdot (w_D - w_E) \geq c, \tag{9}$$

where the worker evaluates the perceived wage return against the cost of training, c. Thus, if the manager is a high X-type and/or the wage gap is adequately large, all workers reporting to the manager will choose to undergo training, and they will be immediately promoted to a difficult job and thus perform difficult tasks. Furthermore, there exists a wage threshold below which no worker will accept to be trained.

Workers can observe the wage gap and their manager's type, X_m. We assume that the firm does not directly observe individual managers' idiosyncratic types, but it knows the distribution of X across all managers. Using this information, the firm can estimate the proportion of workers who will invest in training under a specific wage structure, (w_D, w_E). This share, denoted by $1 - \beta$, is given by:

$$\begin{aligned} 1 - \beta &\equiv \mathbb{P}\left[X \geq \frac{c}{w_D - w_E}\right] \\ &= 1 - F\left(\frac{c}{\varepsilon}\right), \end{aligned} \tag{10}$$

where $F(\cdot)$ represents the cumulative distribution function (CDF) of X and ε represents the wage margin, defined as $\varepsilon = w_D - w_E$. If the X distribution shifts to the right, this will imply a higher share of high X managers, and therefore more trained workers.[69]

K.2 Equilibrium

The firm must determine the optimal wage structure–and, specifically, the optimal wage margin ε to ensure that, for a given α, enough workers decide to be trained.[70] The firm also needs to ensure that workers are willing to work a sufficient number of hours. To account for these multiple margins of decision, we embed the basic promotion setup discussed earlier in a richer model to derive equilibrium conditions for workers' training and hours decisions and the firm wage policy.

[69] We can extend this framework to account for the manager training cost, which reflects the effort required to train workers under a manager's supervision. This cost would shift the distribution of managers toward lower values of X, indicating a reduced inclination to promote employees. Alternatively, we could assume a discrete distribution of managers and incorporate this training cost into the model. Both approaches yield consistent qualitative results.

[70] If the wage margin is very high, all workers are expected to train; however, this would not necessarily be optimal for the firm unless the α is very high, since these workers would also need to be paid more.

The timing of the game is the following:

1. **Wage Setting**: The firm determines the wage levels for both difficult (D) and easy (E) jobs.

2. **Training Decision**: Workers decide whether to invest in firm-specific training by comparing the perceived wage increase associated with being assigned to the D job against the cost of training, and they are promoted immediately if they train in the same period.

3. **Work Hours Determination**: Based on their wage level, which is determined by their training investment and job assignment, workers decide their optimal number of work hours, balancing the utility gained from increased income against the disutility of reduced leisure time.

We solve the model by backward induction, starting with the worker's problem.

K.2.1 Worker's Problem

Labor supply After deciding whether to invest in training, workers are assigned to a job $j \in \{E, D\}$, and determine the optimal number of working hours by solving the following optimization problem:

$$\max_{p,l} p^{(1-\sigma)} l^{\sigma} \quad \text{subject to} \quad p \le m_0 + w_j h \quad \text{and} \quad T = l + h, \tag{11}$$

where p represents consumption, l denotes leisure time, m_0 is a constant representing the base income, w_j is the wage rate for workers in job $j \in \{E, D\}$, and h is the number of hours worked. The parameter σ captures the elasticity of substitution between leisure and consumption. A higher σ indicates that workers are more willing to substitute leisure for consumption, meaning they adjust their leisure more readily in response to wage changes.[71]

The optimal level of consumption and leisure derived by solving the optimization problem in (11) is:

$$p_j^* = (1-\sigma)(m_0 + w_j T) \quad \text{and} \quad l_j^* = \sigma(m_0 + w_j T)/w_j. \tag{12}$$

The optimal level of leisure, l_j^*, decreases as the wage rate w_j increases, reflecting that higher wages incentivize workers to allocate less time to leisure and more to work. However, there is a minimum level of leisure time, σT below which workers cannot go, regardless of the wage level.[72]

Since total time is constrained by $T = l + h$, the optimal number of working hours, h_j^*, is:

[71] If $\sigma = 0$ workers exclusively focus on maximizing consumption while completely neglecting leisure.

[72] Likewise, optimal consumption increases with w_j, since a higher wage raises total income, enabling greater spending.

$$h_j^* = T - l_j^* = (1-\sigma)T - \sigma m_0/w_j, \tag{13}$$

which increases with the wage w_j and is bounded above by $(1-\sigma)T$.

K.2.2 Firm's Problem

Using (7) and (13), the aggregate output of the firm, $\tilde{y}(s)$, with s-type workers is given by:

$$\tilde{y}(s) = h(s)\left(\alpha y_D(s) + (1-\alpha)y_E(s)\right) = h(s)y(s),$$

where $y(s)$ represents the per-unit-time output of a worker, as defined in (7), given a fraction α of difficult jobs, and

$$h(1) \equiv h_D = (1-\sigma)T - \sigma m_0/w_D \quad \text{and} \quad h(0) \equiv h_E = (1-\sigma)T - \sigma m_0/w_E, \tag{14}$$

where h_D and h_E represent the optimal number of working hours for workers in difficult and easy jobs, respectively, as derived in (13).

The firm determines the wage structure that maximizes its net profits by backward induction:

$$\max_{\varepsilon} \pi(\varepsilon) = \max_{\varepsilon} \left(1-\beta(\varepsilon)\right)\left(\tilde{y}(1,\varepsilon) - w_D\right) + \beta(\varepsilon)\left(\tilde{y}(0) - w_E\right), \tag{15}$$

where ε represents the wage margin, defined as $\varepsilon = w_D - w_E$. By choosing an optimal ε, the firm aims to balance two competing objectives: a) incentivize training—setting a sufficiently large wage margin ($\varepsilon > c$) encourages more workers to invest in training, improving productivity; b) minimize costs—a higher wage margin increases labor costs.

We introduce the following assumption to ensure the firm's profit maximization problem has a well-defined solution.

Assumption 1. *The difference in output between trained and untrained workers satisfies the following inequality:*

$$y(1) - y(0) > \frac{c}{T - \sigma/m_0}.$$

Proposition 1. *Suppose that Assumption 1 holds. Then, there exists an interior maximizer $\varepsilon^* > c$ for the firm's optimization problem in (15). Moreover, if σ is sufficiently small and Assumption 1 is satisfied, this maximizer ε^* is unique.*

Proof See Section K.4

K.2.3 Implications

The model yields the following insights.

1. As in Prendergast (1993), the firm has an incentive to offer a wage margin for D jobs to incentivize workers to train and acquire firm-specific skills. Since $w_D > w_E$, Equation 13 implies that trained workers will work more hours than untrained workers in equilibrium.

2. For a given wage structure, teams reporting to different managers will vary in training take-up. These differences stem from variations in managers' abilities to communicate and persuade workers to invest in training as a pathway to promotion. In equilibrium, the ratio $\frac{c}{\varepsilon^*} \in (0,1]$ serves as a threshold distinguishing managers whose workers engage in training from those whose workers do not. This threshold represents the indifference point. Specifically, if X_m and $X_{\tilde{m}}$ are two managers such that $X_m < \frac{c}{\varepsilon^*} < X_{\tilde{m}}$, the workers under manager X_m will remain untrained and work fewer hours. In contrast, the workers under manager $X_{\tilde{m}}$ will undergo training and work more hours.

3. Higher training costs c reduce the marginal impact of wage increases on training take-up. This implies that firms operating in environments with high training costs face even greater constraints in leveraging wage incentives to drive higher profits.

4. Proposition 1 implies that having a higher share of trained workers has a positive effect on profits, as long as $\varepsilon \leq \varepsilon^*$ (i.e. the wage margin is less than or equal to the optimal wage margin).[73] However, if ε is greater than ε^*, production increases would be offset by a reduction in profitability, since trained workers are assigned to D jobs, which have higher wages.

5. If $\varepsilon < \varepsilon^*$, the marginal effect on profits of increasing the wage differential between D and E jobs is bounded.[74] That is, further wage increases to entice workers to train for difficult jobs yield diminishing returns in terms of profit gains.

[73] This follows from the fact that to the left of a maximum, the first-order derivative of the profit function (23) is expected to be positive. In our context, this means that when the wage margin is below its optimal level, any increase in the wage margin will result in higher production.

[74] The derivative of the profit function with respect to ε is bounded above by:

$$\frac{\partial \pi}{\partial \varepsilon} \leq \frac{1}{c} f\left(\frac{c}{\varepsilon}\right)(y(1)-y(0)) \leq \frac{M}{c}(y(1)-y(0)), \tag{16}$$

where $M = \max_{x\in[0,1]} f(x)$ represents the maximum value of f over the interval $[0,1]$.

K.3 Exogenous increases in α

We model the demand shock examined in Section 5 as an exogenous increase in α, the share of D jobs needed in production. We analyze the implications of this change for workers' effort and firm production in both the long run (when wages can change) and the short run (when wages are fixed).

K.3.1 Long run effects

First, we study the long term impact of a change in α on the optimal wage margin, ε^*, in the next corollary.

Corollary 1. *Let ε^* be the optimal wage margin from Proposition 1. Then,*

$$\frac{\partial \varepsilon^*}{\partial \alpha} > 0.$$

Corollary 1 shows that an increase in α raises the incentive to increase the wages of difficult jobs (w_D, and hence the wage differential ε). Intuitively, this happens for two reasons. First, to incentivize workers assigned to difficult jobs to increase their work hours (as defined in (13)). Second, to motivate more workers to invest in firm-specific training to be promoted to D jobs.[75]

However, the firm will not increase the optimal wage margin if the increase in α lowers profits. The net effect on profits of an increase in α depends on two margins:

- The fraction of workers who are already trained. If, in equilibrium, only a small share of workers have trained to perform difficult tasks prior to the increase in α, then this will translate into small changes in production and, therefore, profits.

- The relative advantage of a trained ($s = 1$) and untrained ($s = 0$) worker, $\Delta(s)$. This relative advantage is defined as the increase in productivity of assigning a trained (untrained) worker to a difficult (easy) task compared to an easy (difficult) task

$$\Delta(s) \equiv (-1)^s \left(y_E(s) - y_D(s)\right). \tag{17}$$

  We further define $(s + (-1)^s \beta(\varepsilon))\Delta(s)$ as the relative advantage of a type s worker weighted by the fraction of workers of such type inside the firm.

Using the Envelope Theorem to differentiate (15), we get,

[75] Formally, the cross-partial derivative of the profit function with respect to both α and ε is positive.

$$\begin{aligned}\frac{\partial \pi}{\partial \alpha}(\varepsilon^*) &= (1-\beta(\varepsilon^*))\,h(1)\Delta(1) - \beta(\varepsilon^*)\,h(0)\Delta(0) \\ &= (1-\beta(\varepsilon^*))\,h(1)\Delta(1)\left(1 - \frac{\beta(\varepsilon^*)}{1-\beta(\varepsilon^*)}\frac{h(0)}{h(1)}\frac{\Delta(0)}{\Delta(1)}\right).\end{aligned} \tag{18}$$

We summarize the results in the following corollary.

Corollary 2. *Let $\pi(\varepsilon,\alpha)$ be the firm's profits for a given wage gap ε and the proportion of difficult problems α. Then,*

1. *$\frac{\partial \pi}{\partial \alpha}(\varepsilon^*)$ is monotone increasing with respect to ε,*
2. *$\frac{\partial \pi}{\partial \alpha}(\varepsilon^*) > 0$ if $\beta(\varepsilon)\Delta(0) < (1-\beta(\varepsilon))\Delta(1)$.*
3. *$\frac{\partial \pi}{\partial \alpha}(\varepsilon^*) < 0$ if $\beta(\varepsilon)\Delta(0)h(0) > (1-\beta(\varepsilon))\Delta(1)h(1)$.*

The first result of Corollary 2 highlights that the sensitivity of profits to changes in α in equation (18) is monotonically increasing with the wage gap ε. This implies that, when the wage gap is small, an increase in α may reduce profits, as the incentives for workers to train are weak. However, as the wage gap increases, profits respond more favorably to increases in α, eventually reaching a point where the firm can achieve a net positive effect by encouraging more workers to train.

Both the second and third results discuss sufficient conditions under which the sign of (18) can be determined. Specifically, the second result establishes that if the weighted relative advantage of trained workers exceeds that of untrained workers, the firm's profits increase with α. This condition implies that when trained workers are significantly more productive in complex tasks than untrained workers are in simple tasks, an increased demand for difficult jobs leads to higher wage margins and a larger share of workers capable of performing these tasks, thereby boosting profits. Hence, firms operating in environments where specialized skills are highly valuable will find it profitable to promote training and specialization as α rises.[76]

The third result provides the counterpart condition, offering a necessary and sufficient condition for which (18) is negative. This occurs when the weighted relative advantage of untrained workers is greater than that of trained workers, which can happen if the fraction of trained workers is relatively low, or if the productivity advantage of untrained workers exceeds that of trained workers.

[76]An important observation is that the impact of α is driven by productivity differentials between trained and untrained workers, rather than differences in labor supply since trained workers consistently work more hours than their untrained counterparts.

K.3.2 Short run effects

While the firm can commit to a future increase in the wage margin ε, it may not be able to do so in immediately after the increase in α. This is the case for the firms in our sample: wages are usually adjusted annually for the quick service restaurant chain and retail company, and require extensive union negotiations for the car company. Thus, to reach the production levels needed to meet the demands of a higher α, the firm may need to combine the announcement of a future increase in wages with an immediate increase in contracted hours (h_j^c), while keeping the wage schedule constant. We now consider the effects of this scenario on workers' effort, their incentive to train, and firm's profits.

Effects of the increase in contracted hours with constant wages If wages are constant, the impact of an increase in contracted hours h_j^c on firm's production may be modest if they exceed the worker's optimal labor supply h_j^*.[77] This is because, by increasing hours without changing wages, the firm pushes workers to a point in which the rate of substitution between income and leisure exceeds the slope of their budget constraint (w_j). Workers may thus engage in absenteeism to get closer to their equilibrium hours or leave the firm all together.[78] The average increase in absenteeism and turnover will depend on the new level of contracted hours imposed by the firm.[79]

The incentive to be absent is less pronounced for trained workers—who are assigned to difficult jobs, and hence earn a higher wage—compared to untrained workers. Therefore, since high X managers have a higher share of trained workers, they will be less likely to see an increase in absenteeism.

Effects of the anticipated wage increase The anticipated increase in ε will make training more attractive for untrained workers. Let the anticipated wage increase for D jobs be γ, such that the wage differential becomes $\varepsilon + \gamma$. In the short run, after training occurs, but prior to the actual

[77]If $h_j^c < h_j^*$, that is, if contracted hours are below the worker's optimum, an increase in the number of contracted hours will increase firm's production due to the workers' willingness to increase their effort in order to meet their consumption needs.

[78]For the worker to stay employed, contracted hours need to be such that workers' consumption utility is higher when working rather than being unemployed. Denoting the upper bound for the stipulated working hours beyond which the worker will refuse the contract as $\bar{h}_j$, if the worker is employed then it has to be that $h_j^c < \bar{h}_j$. Formally, a worker will accept the contract for the job j as long as it provides more utility than being unemployed, that is:

$$m_0^{1-\sigma} T^{\sigma} < [m_0 + w_j h_j^c]^{1-\sigma} (T - h_j^c)^{\sigma}. \tag{19}$$

From this:

$$\bar{h}_j = T\left(1 - \frac{\sigma m_0 / w_j T - \sigma}{1-\sigma}\right)$$

[79]The temptation to be absent grows in the number of stipulated contracted hours, h^c, since the disutility from the gap between h^c and h_j^* grows as h^c increases.

increase in w_D, the firm's profit is:

$$\pi(\varepsilon,\gamma) = (1-\beta(\varepsilon))\left(\tilde{y}(1,\varepsilon+\gamma)-(w_E+\varepsilon)\right) + \left(\beta(\varepsilon)-\beta(\varepsilon+\gamma)\right)\left(\tilde{y}(1,\varepsilon+\gamma)-w_E\right) \\ +\beta(\varepsilon+\gamma)\left(\tilde{y}(0)-w_E\right), \tag{20}$$

where the first term represents profits from workers who had already committed to investing in training before the increase in α; the second term represents profits from the portion of $(\beta(\varepsilon)-\beta(\varepsilon+\gamma))$ workers who have invested in training in anticipation of a promotion and a raise to $w_D+\gamma$. Crucially, while these workers are still paid as untrained workers, they have already acquired the skills needed to perform D tasks.[80] The third term accounts for profits from the portion $\beta(\varepsilon+\gamma)$ of workers who choose to remain untrained.

By differentiating equation (20) with respect to γ, we get:

$$\frac{\partial\pi}{\partial\gamma} = \frac{c}{(\varepsilon+\gamma)^2} f\left(\frac{c}{\varepsilon+\gamma}\right)\left(\tilde{y}(1,\varepsilon+\gamma)-\tilde{y}(0)\right) + \frac{\sigma m_0}{(\varepsilon+\gamma+w_E)^2} y(1)\left(1-\beta(\varepsilon+\gamma)\right) > 0, \tag{21}$$

which indicates a positive correlation between training and profits (as well as output) in the short term.

We can compare the long run effect on an increase in the wage differential $w_D - w_E$ with that of an increase in γ, when $\gamma \to 0$, representing the anticipation of a minimal wage increase.[81] Formally, this amounts to comparing (21) with the derivative of the profit function with respect to ε, as shown in Section K.4 equation (23). The difference between short-term and long-term effects on profits is given by:

$$\left.\frac{\partial\pi}{\partial\gamma}\right|_{\gamma=0} - \frac{\partial\pi}{\partial\varepsilon} = \frac{c}{\varepsilon} f\left(\frac{c}{\varepsilon}\right) + \left(1-F\left(\frac{c}{\varepsilon}\right)\right). \tag{22}$$

This expression is positive for $c \leq \varepsilon < \varepsilon^*$, indicating that the expectation of a wage increase leads more workers to train and perform D jobs. Since wages remain constant, profits increase in the short run. In the long term, as wages adjust to their optimal level (ε^*), the correlation between training (share of newly trained workers) and profits weakens, reflecting the reduced marginal impact of wage increases on profits.

Note that the positive effect of the wage increase on training still depends on the managerial type, X_m. If a high X manager leaves after a demand shock and is substituted by a low X manager,

[80] The implicit assumption is that the promotion and the wage increase will happen at the same time in the next period.

[81] The condition $\gamma \to 0$ reflects minimal anticipation, where workers expect slight wage adjustments. This scenario contrasts with the long term, where actual wage increases occur.

the incentive to train will be dampened. This is because the difference between the hours worked under the anticipated wage increase $w_D + \gamma$ and the hours they are willing to work at their current wage w_E is

$$\Delta h \equiv h(1, w_D + \gamma) - h(0) = \frac{\sigma m_0(\varepsilon + \gamma)}{w_E(\varepsilon + w_E + \gamma)},$$

where Δh measures the temptation to be absent.

K.3.3 Implications of a change in α

To summarize, the model yields the following predictions.

1. In the long run, an increase in α increases the firm's incentive to commit to a higher wage schedule for difficult, D, jobs. The expected increase in w_D will increase the incentives to train.

2. For a given wage schedule (i.e., in the short run), an increase in α (the share of complex tasks needed in production) will result in higher profits only if there is a sufficiently large fraction of units with trained workers, $(1 - \beta)$, and if the productivity gains from training, $(y_D(1) - y_E(1))$, are high enough. If this is not the case, in the short run (i.e. when wages are fixed), an increase in α will lead the firm to increase the number of contracted hours. If contracted hours are above the workers' optimal hours, however, this change may be offset by an increase in absenteeism.

3. Given the wage structure and assuming the same contracted hours for all workers, the tendency to be absent will be higher for untrained workers in easy jobs than for trained workers in difficult jobs.

4. Teams reporting to high X managers will experience a smaller increase in absenteeism due to a) the presence of more trained workers (who are assigned to higher paid D jobs); and b) the fact that untrained workers will have a greater incentive to get trained once the firm commits to a higher w_D.

K.4 Proofs

Proof of Proposition 1. Suppose that Assumption 1 holds. Then, the firm's profit function can be written as:

$$\pi(\varepsilon) = \left(1 - F\left(\frac{c}{\varepsilon}\right)\right)(h(1,\varepsilon)y(1) - (w_E + \varepsilon)) + F\left(\frac{c}{\varepsilon}\right)(h(0)y(0) - w_E).$$

To find the maximum, we calculate the derivative of $\pi(\varepsilon)$ with respect to ε:

$$\frac{\partial \pi}{\partial \varepsilon} = \frac{c}{\varepsilon^2} f\left(\frac{c}{\varepsilon}\right)(h(1,\varepsilon)y(1) - h(0)y(0) - \varepsilon) + \left(1 - F\left(\frac{c}{\varepsilon}\right)\right)\left(\frac{\sigma m_0 y(1)}{(w_E + \varepsilon)^2} - 1\right). \tag{23}$$

Evaluating this derivative at $\varepsilon = c$, we get

$$\left.\frac{\partial \pi}{\partial \varepsilon}\right|_{\varepsilon=c} = \frac{1}{c} f(1)\,(h(1,c)y(1) - h(0)y(0) - c).$$

As Assumption 1 holds, we have that $h(1,c)y(1) - h(0)y(0) > c$. This inequality implies that the derivative $\frac{\partial \pi}{\partial \varepsilon}$ is positive at $\varepsilon = c$. On the other hand,

$$\lim_{\varepsilon \to \infty} \frac{\partial \pi}{\partial \varepsilon} = -1,$$

which guarantees the existence of an interior maximum. Uniqueness can be established by considering the case where σ is small and treating it as a perturbation from the case where workers dedicate all their time to work.

□

Proof of Corollary 1. Applying the Implicit Function Theorem on (23), we get that the partial derivative of ε^* is a quotient between the mixed derivative of the profit function over the second derivative with respect to ε, which we assume is negative, given that we are evaluating on a maximum. Then,

$$\frac{\partial \varepsilon^*}{\partial \alpha} = -\left[\frac{\partial^2 \pi}{\partial \varepsilon \partial \alpha}\right]\left[\frac{\partial^2 \pi}{\partial \varepsilon^2}\right]^{-1}. \tag{24}$$

Since

$$\frac{\partial^2 \pi}{\partial \varepsilon \partial \alpha} = \frac{c}{\varepsilon^2} f\left(\frac{c}{\varepsilon}\right)\frac{\partial}{\partial \alpha}(h(1,\varepsilon)y(1) - h(0)y(0)) + \left(1 - F\left(\frac{c}{\varepsilon}\right)\right)\frac{\sigma m_0}{(\varepsilon + w_E)^2}\frac{\partial}{\partial \alpha} y(1) > 0, \tag{25}$$

the sign of equation (24) is positive. □

We now examine how the equilibrium wage margin ε varies as a function of changes in the distribution of managerial types. From equation (23) and the limiting conditions derived below it, we know that in equilibrium (given uniqueness), the first term in (23) is positive, while the second term is negative. Consider a rightward shift in the distribution of managers, meaning that the density function f concentrates more mass near 1 and exhibits a steep decline in that region (this is equivalent to having a higher likelihood of high-X managers). Mathematically, this implies that $f(c/\varepsilon)$ decreases rapidly as ε increases. Consequently, the equilibrium condition (23) is met at a lower value of ε, suggesting that the optimal wage margin converges toward c. Conversely, when the distribution of managers shifts leftward, f is small near 1, but by Assumption 1, the first term of (23) remains positive and dominates the second term when ε is close to c. The only way for (23) to hold at equilibrium is for ε to increase. This process continues until either the wage gap becomes too large to sustain—resulting in downward pressure from the $-\varepsilon$ term in (23)—or until the rise in f counterbalances this effect.

In summary, the equilibrium wage margin ε is expected to be higher when the distribution of managers is shifted to the left and lower when it is shifted to the right.