Training within Firms*

PRELIMINARY AND INCOMPLETE

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July 23, 2024

Abstract

Training investments are crucial for increasing productivity within firms, yet their implementation often faces challenges such as low participation rates and inadequate worker engagement. This study uses data from three firms–a car manufacturer, a fast-food chain, and a retail company–to examine the role of middle managers in internal training programs. Our findings reveal that middle managers significantly influence training participation among workers, which in turn affects firm performance, especially during periods requiring teams to adapt to new business conditions. In response to an exogenous demand shock necessitating increased employee effort, workers supervised by low-training managers exhibit higher absenteeism, whereas those under high-training managers show no change in absenteeism. The importance of middle management is particularly pronounced for lower-ranked workers, those more impacted by the demand shock, and branches operating in more competitive labor markets.

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

*We thank Oriana Bandiera, Guido Friebel, Wouter Dessein, Miguel Espinosa, Bob Gibbons, Andrea Prat, Virginia Minni, John Van Reenen and participants in seminars at the 2023 Empirical Management Conference, Olin Business School, Rochester, Bocconi, HBS D^3 Research Symposium, LSE, LBS, MIT Sloan, Kellogg, USC, CESifo Summer Institute for their valuable comments. We thank Jessica Avellaneda, Paula Neira, Andres Felipe Rengifo, David Rodriguez-Gonzalez, and Peter Li, for excellent research assistance. Sadun and Tamayo gratefully acknowledge funding from Harvard Business School and the D^3 Institute. Diaz and Ramirez: Digital Reskilling Lab; Neyra-Nazarrett: Harvard University; Sadun: Harvard University, Digital Reskilling Lab, NBER and CEPR; Tamayo: Harvard University and Digital Reskilling Lab.

1 Introduction

Training is vital for enhancing both firm and worker productivity by equipping employees with necessary skills and knowledge, leading to improved job performance and organizational efficiency (Adhvaryu et al., 2023b,c; Bartel, 1994, 1995; Dearden et al., 2006; Espinosa and Stanton, 2022; Konings and Vanormelingen, 2015). Understanding the heterogeneity in training investments *across* firms, despite their benefits, has been of interest to the economics literature since Becker (1964) seminal work on human capital theory.[1] However, the complexities involved in the implementation and evaluation of training programs *within* firms are less understood.[2] While many organizations acknowledge the benefits of training and are increasingly investing in employee development (Desjardins, 2023; Tamayo et al., 2023), the scant available evidence indicates that the actual implementation of these investments is fraught with difficulties, starting from low participation rates and adverse selection of the participants.[3]

This paper contributes to the existing literature by studying with unprecedented detail the implementation of training programs within three large organizations based in Latin America–an Argentinian car manufacturer with approximately 1,800 employees, a fast food chain with 2,500 employees, and a large retail company with 25,400 employees, both based in Colombia. For each of these firms, we have access to rich administrative data that allow us to measure with precision who gets trained, what type of training programs are taken up, as well as reporting relationships between employees and managers within the firm. The data also provide information on performance at the team level, as well as detailed HR outcomes such as employees' absenteeism and turnover. These unique data allow us to study within-firm variation in the implementation and effectiveness of internal training programs, shedding new light on whether and how internal organizational frictions impact training outcomes.

We study firm-specific, operational training programs, which are centrally designed by the HR department to enhance worker productivity in specific roles. Each firm in our study compensates workers for the time spent in training. However, firms do not directly compensate workers for the acquisition of firm-specific skills, opening the door to double moral hazard issues discussed in Kahn and Huberman (1988). That is, workers train only if there is a promise for a higher wage if they do so, but the firm has an incentive to claim that workers have not acquired the skill (even if they did)

[1] Subsequent studies have built on Becker's theory, discussing, for example, the role of labor market imperfections in driving the decision on whether to invest in training (Acemoglu and Pischke, 1999; Leuven, 2005).

[2] Bartel (1995) and Krueger and Rouse (1998) leverage firm-level data to study the impact of training on workers' wages and performance. However, differently from this paper, they do not examine heterogeneity in training implementation within the firm.

[3] Leuven and Oosterbeek (2008) highlight the low participation rates in voluntary training programs, while Barron et al. (1997) discuss the difficulties in measuring training effectiveness. Sandvik et al. (2021) find that voluntary training programs attract the best employees, who benefit the least from it.

to save on wages. Workers anticipate that firms will renege on their promise, and as a consequence they don't participate in training. In line with Prendergast (1993), the firms in our study attempt to address this problem by committing to a promotion-based compensation that implicitly rewards skills acquisition: training programs are internally presented to employees as essential for career development, including both lateral and upward moves. Despite this messaging, however, training take-up is highly heterogeneous across workers within the firms, suggesting that other frictions may be at play.

The paper focuses on the role of middle managers as a possible source of variation in training take-up within firms. While the courses are typically imparted by specialist trainers, middle managers are often the ones suggesting training opportunities to workers and are in charge of certifying their newly acquired skills after training. Therefore, differences in managerial behavior–e.g., how actively they recommend training opportunities or how lenient they are in the certification stage–could shape workers' perceptions of the value of training and, thus, their participation in training activities. Since middle managers are not directly compensated or monitored for training take-up in their teams, whether they support training depends on their perceived trade off between the benefits of having a more skilled team and the costs involved, i.e., employees not working while being trained, the time spent coaching them and certifying their skills, and the possible loss of skilled employees to other teams if training raises their chances of being promoted. This implies that different middle managers within the same firm may have very different stances on employees' training, potentially undermining the incentives set up by the central HR function. Even worse, central HR commitment to rewarding training with future promotions may run completely opposite to the interests of middle managers engaged in talent hoarding, as in Haegele (2022).

Our analysis shows that middle managers play a crucial role in the implementation of firm-specific, operational training programs. We find significant differences in training take-up rates and subsequent performance outcomes in teams, and we show that these differences are strongly related to the identity of the middle manager in charge of the team. Specifically, exploiting the fact that managers are routinely rotated across teams, we find that middle managers have large variations in training "value added," significantly influencing employees' training participation rates. 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. We find that training take up increases significantly 8 weeks after the arrival of a HT manager, by 45% for the car manufacturing firm, 55% for the fast food chain and 60% for the retailer. Taken together, these findings suggest that middle managers are critical to translate central HR policies and career opportunities to front-line workers, even if this role is not explicitly recognized in their compensation.

Thanks to auxiliary survey data self-reported by the managers collected in one of the firms, we show that HT managers are sharply distinct from others in terms of some personal characteristics (social skills and extroversion) and management practices. Namely, they are more likely to involve their employees in decision-making, engage in retrospective learning, focus their attention on weak performers as opposed to stars, and be more preoccupied with workers' engagement and well-being. This suggests that managerial heterogeneity in training is correlated with a broader set of activities and attitudes. Broadly, HT managers appear to focus their attention on teams rather than high-performing individuals.

In the second part of the analysis, we turn to examining the impact of HT managers on performance. Teams led by HT managers are not significantly more productive than others when the teams face normal business conditions. This is consistent with the idea that middle managers are horizontally, rather than vertically differentiated. That is, a similar level of performance may be achieved with different combinations of managerial and workers' inputs. However, we show that teams led by HT managers show better performance in the aftermath of a large and positive demand shock that exogenously increased workload requirements across all three firms. In the car company, the demand shock consists of two centrally imposed production expansions by the CHQ: the first increased production by approximately 27%, and the second by about 38%, while for the retailer and fast food chain, it is the staggered roll-out across stores of a partnership with a last-mile delivery service that increases transactions by 3 and 6 percent, respectively. Workers were not compensated for the extra effort needed to perform their jobs. Consistently with standard labor supply theory, we find that across the three firms, these demand shocks were followed by a large increase in workers' absenteeism. This effect, however, did not occur for HT managers, who did not experience any significant change in absenteeism despite facing the same increases in workload. These findings are consistent with the idea that the benefits of HT managers are contingent on the need for change and adaptation.

To better understand the role of HT managers in mediating the impact of the demand shock, we study the heterogeneity in the response to the shock across units within and across teams. We find that the impact of HT managers on performance and absenteeism during the demand shock was especially large for employees with lower training take-up before the shock, in lower levels of firms' hierarchy, and in occupations that were especially exposed to the shock. We also study the relevance of heterogeneity across teams and find that HT managers were especially relevant in locations in which workers had better outside options, i.e., where labor markets were more competitive. Finally, using a setup similar to Bandiera et al. (2018), we show that HT managers played a similar role in reducing absenteeism in the aftermath of a different shock to the cost of effort–a sudden and large increase in rainfall in the vicinity of the workplace.

Overall, this paper suggests that the centrally designed training programs face significant frictions in implementation, and emphasizes the critical role of middle managers in translating centrally designed HR policies to workers. This finding has important implications for both researchers interested in evaluating training investments, and for practitioners seeking to enhance the effectiveness of training investments in improving productivity. For example, they suggest that training programs should be designed in such a way that proactively enlists middle managers in their implementation.[4]

This study builds on previous research on training and productivity (Adhvaryu et al., 2023b,c; 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 is able to 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., 2023d; Bloom et al., 2014, 2012; Bloom and Van Reenen, 2010; Friebel et al., 2023; Hoffman and Tadelis, 2021; Metcalfe et al., 2023), 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 burgeoning 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). The contribution of this paper relative to the existing literature in this area is to show that the value of middle managers extends to training, and in studying the contingent performance effects of middle managers on workers' absenteeism.

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.

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 Sections 5 and 6 present the results related to the role of HT managers for performance and the heterogeneity analysis in relation to the demand shocks. Section 7 shows the effects of HT for the rainfall shock. Section 8 concludes.

[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).

2 Context

In this section, we describe the basic characteristics of the three firms included in the study: a car manufacturer in Argentina, a fast food 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, and their training programs.

2.1 Production Activities

Car Manufacturer The car manufacturer is the Argentinian subsidiary of a global company engaged in the production of a wide range of automotive models. The firm operates an assembly plant located in Argentina, employing 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.[5] 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 sectors. These parts are then assembled together in the Assembly sector, which is one of the most delicate phases of production.[6] 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.

Fast-food chain The fast-food chain is the Colombian subsidiary of a large multinational company. The firm employs $2,500$ workers across 83 stores nationwide.

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 (including condiments), soda fountain, and desserts. Each employee is typically 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-thru 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 is organized to ensure timely service and high quality standards in service.

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

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

Retailer The retail company is the Colombian subsidiary of a Latin American firm, employing 25,400 workers across 83 stores.

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 make sure 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).

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 fast food chain).[7] 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.[8] The specific role of middle managers varies slightly across firms is described in Section A.1.

2.3 Training and Managerial Rotations

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

[7] All three firms would rate highly in the management score of Bloom and Van Reenen (2010) in terms of the adoption of operational and HR management practices

[8] Middle managers' influence varies slightly across the three companies: promotion decisions are relatively more centralized in the car manufacturer than in the fast-food chain and the retail company.

to our study, training policies and managerial rotations.

First, the three firms 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.[9] 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 structure is meant to foster continuous learning and skill development, encouraging workers to progress in their careers and take on more complex and responsible roles over time.[10] Although training is conducted by dedicated staff, middle managers may recommend training to workers and have to certify skills acquisition after completion. Middle managers are not directly compensated for workers getting trained or any other training-related activity.[11]

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.[12] 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 fast food 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 importance of middle managers for training take-up, in isolation from other team or workers' characteristics.

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,

[9] The specific content of the programs is described in Appendix A.2.

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

[11] We made multiple visits to the three companies and conducted interviews with over 15 middle managers at each company. In several instances, managers talked about their effort in promoting training opportunities to their employees as opportunities for career advancement within the organization. The motivation behind this was often the fact that they took pride in being advocates of talent development within the firm. We will come back to a more precise characterization of middle managers investing in training in Section 4.

[12] This was reported to us by the firms and we also verify that this is the case in the empirical analysis.

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 positions) and unit (team or store) within the company. Leveraging these data, we are able to 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 (See Appendix A.2).

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 fast food 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, 83 stores for the fast food chain, and 83 stores for the retailer.

Auxiliary data For the fast food chain, we collected self-reported data on middle manager traits and management practices with a detailed online survey designed and implemented in partnership with the organization. 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 was conducted in March 2023, achieving a 90% response rate, with 378 managers participating.[13]

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 (see Section 7). 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 the total rainfall. This dataset includes daily measurements of rainfall and temperature from 303

[13] 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.

stations. We assign weather variables to municipalities where the fast food chain and retail company have a presence, using inverse-distance weighting.

3.2 Summary Statistics

In this section, we present the annual summary statistics for the main variables used in the analysis for three companies over different periods. We focus on performance measures, key HR metrics, and training statistics. Table 1 presents the summary statistics for the main variables used in the analysis.[14]

Car Manufacturer To calculate the total number of cars produced at the plant level, we use operational records. On average, around 105,000 cars are produced each year across the plant. 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 are substantial and typically involve formal technical training outside of the production line. Annually, about 22 training programs are initiated, training 17% of the workforce, with an average of 2.9 programs per employee. Just less than half of these programs are on the job and technical in nature: 9.80 training sessions annually, with 11 percent of employees trained, averaging 1.8 technical training programs per employee.

Fast-Food Chain Using scanner-level data from store sales, we construct a measure of productivity based on total sales at the annual period level. Throughout the paper, we use the number of tickets and the units sold as alternative measures of productivity. The Number of tickets is the number of total orders fulfilled by the store at a given period, and the units are the individual items within an order. On average, each store sells around $963,000$ US dollars a year, around 614,000 units (these are the particular elements or items in an order), and around 241,000 tickets are sold per year per store.

A store generally has around 22 workers at any point in 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 12 percent of the labor force of a store. Each year, 9 employees leave the store, 14 are hired, and 6 are promoted.

[14] 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 fast food and retail companies we use total sales at the store level.

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

	Car manufacturer		Fast food 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)			963.49	513.43	20,595	16,727
Units sold (Num. of units sold)			614,709	331,207	4'417,662	3'488,097
Number of tickets (Num. of completed orders)			241,232	134,485	3'019,110	2'273,481
Sales per Employee ('000 of US dollars)			45.877	19.620	215.513	77.552
HR Measures (Unit level)						
Workers per unit	14.66	8.21	22.56	10.91	112.94	101.55
Employee tenure (years)	7.75	5.38	1.31	1.44	4.27	6.98
Share employees ever absent in the year	0.44	0.34	0.61	0.15	0.45	0.46
Number of absent employees (biweekly average)	1.03	0.77	2.98	2.14	6.49	7.31
Share absent employees (biweekly average)	0.07	0.05	0.12	0.05	0.051	0.03
Turnover (Num. of employees exiting, annual cumulative)	1.62	3.78	9.15	6.89	44.33	59.72
Hired (Num. of employees hired, annual cumulative)	5.48	8.30	14.83	9.79	47.42	68.17
Promotion (Num. of promoted employees, annual cumulative)	7.55	9.13	5.75	2.80	14.36	12.05
All training (Unit level, annual cumulative)						
Average n. of training programs started	22.08	29.50	332.28	162.78	138.41	129.02
Share of trained employees	0.17	0.16	0.82	0.14	0.26	0.09
Training programs per employee	2.90	1.28	12.8	3.1	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	

Table 1 reports the summary statistics for each company on productivity, absenteeism, tenure, turnover, hiring, and promotions in an annual period. For the car company, we analyze the period between January 2017 and October 2019 through 196 working groups; for the fast food chain, the analysis is done between June 2018 and November 2019 for 83 stores. Finally, for the retail company, we consider 83 stores from January 2017 to March 2020. The table reports the summary statistics for each company on total training programs started as well as operational training, which is the focus of our analysis in the subsequent sections. For each company, we analyze the average number of training programs started, the share of workers trained, and the number of training programs per employee on a given year for each unit (working group in the car company and store for the fast food chain and retail company).

Training programs in the fast food 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 332 training programs are started on average, and 82 percent of the workforce is trained, averaging 12.8 training programs per employee.

Retailer We use scanner-level data from store sales to calculate total sales, number of units sold, and total ticket or receipt at the store level. On average, around $20.6 million US dollars are sold each year 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 are substantial and involve both on-the-job training to manage stations and overall store operations. In a given year, 138.41 training programs are started on average in a store, with 26 percent 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 percent of employees trained, averaging 1.13 training programs per employee.

3.3 Within Firm Variation

In addition to the significant heterogeneity across firms, we see considerable within-firm variation in 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, 12% for the fast food chain, and 5.2% for the retailer, there are large variations across units: 5% for the car manufacturer and the fast food 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, 61% (15%) for the fast food 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.

Similarly, training take-up is also heterogeneous within firms. For example, the mean (standard deviation) of the share of trained employees in the team is 17% (16%) in the car company, 82% (14%) for the fast food 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 shows that centralized HR policies have 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.

4 Estimating the Role of Middle Managers for Training

4.1 Identifying Managerial Fixed Effects in Training

Our empirical analysis starts by estimating the value added by managers in training take-up for each unit of analysis (teams for the car manufacturer and stores for the fast-food chain and retailer). By leveraging the routine rotation of managers across units for reasons unrelated to performance and training take-up, we estimate the differences in training take-up across teams attributable to individual middle managers.

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 fast-food and retail companies 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.[15] In the case of the car manufacturer, $\psi_{j(i,t)}$, refers to a worker-fixed effect, and in the case of the fast food 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.

The error term in (1), ε_{ijt}, can be decomposed into a match-specific component, $\eta_{J(i,t)}$; a unit root component, ξ_{it}; and a transitory error, ν_{ijt} (Card et al., 2018, 2013),

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

The identification of manager and store 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 stores based on the permanent components of managerial ability (θ_i) and store components (ψ_J), permitting sorting on these fixed effects.

[15] Training is counted regardless of completion status.

However, it excludes the possibility of managers being assigned to stores 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 worker 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 fast food 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 fast food chain, and 14 CSs for the retail company. We estimate equation (1) within each connected set.[16]

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.[17,18] 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 conducts 1 training program per working group every two weeks. In contrast, a manager at the 90th percentile conducts 6 training programs per working group every two weeks. The numbers are similar for the retail company: a manager in the 10th percentile conducts 2.18 training programs per store every two weeks, while a manager in the 90th percentile conducts 3.78 training programs per store every two weeks. The distribution of fixed effects in the fast-food company shows larger differences. A manager in the 10th percentile conducts 2.1 training programs per store every two weeks, whereas a manager in the 90th percentile conducts 21.55 training programs per store every two weeks.

Our results indicate that managers significantly contribute to the total variance in training within the firm. Figure 2 illustrates the share of the training variance across units that can be attributed to managers and unit fixed effects.[19] For the three companies, the contribution of manager fixed effects to the training variance is higher than that of the unit fixed effects. 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 fast-food chain.

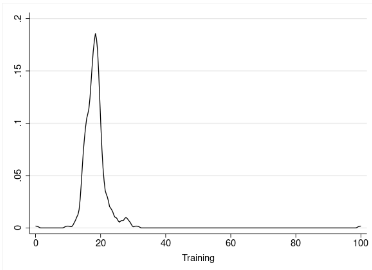
[16] Later in the paper, we analyze the AKM model's limitations and implement several robustness checks and alternative specifications.

[17] 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.

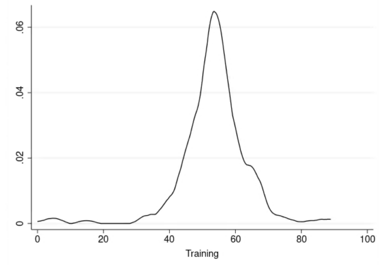
[18] Later in the paper, for comparison purposes, we compare manager fixed effects for training and sales. To do this, we estimate the fixed effects of the units and managers for the fast-food and retail companies using log(sales/employees) as the dependent variable.

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

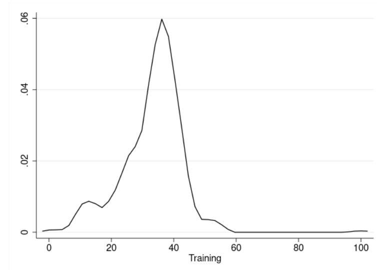
Figure 1: Distribution of Manager Fixed Effects in Training Take-Up Across Firms



(a) Car Manufacturer



(b) Fast Food Chain



(c) Retail Company

Figure 1 shows the manager fixed effects distribution for each company obtained from estimating equation 1, where we use the 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.

Figure 2: Variance decomposition Manager vs. Unit Fixed Effects

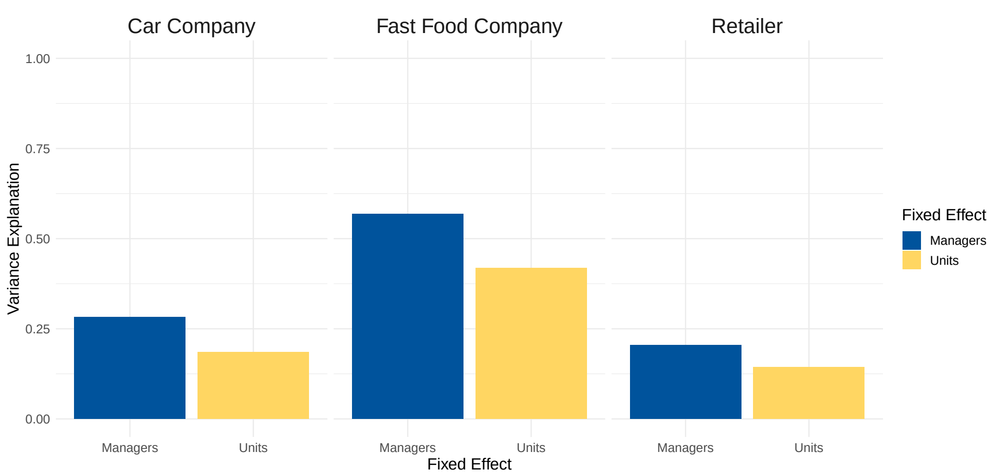


Figure 2 illustrates the proportion of total variance in the training variable across stores (fast food and retail companies) and working groups (car company) that can be attributed to manager and unit fixed effects. We calculate the ratio of variance attributable to manager (blue) and unit (yellow) fixed effects relative to the total variance. A value of 1 indicates that the 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 fixed effects.

4.1.1 Identification Assumptions and Tests

To consistently estimate the parameters in (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 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 store/manager fixed effect requires a strong exogeneity assumption. This assumption implies that the assignment of workers to managers must be conditionally mean-independent of the past, present, and future values of the error term. Consequently, this assumption prohibits any sorting of stores/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 assumptions do allow for sorting based on the fixed effect term or positive assortative matching of workers/managers and managers/stores (Card et al., 2013). To establish the validity of our 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 store fixed effects in the AKM model requires observing a sufficient number of managers over time in different stores, ensuring adequate mobility. Limited mobility bias may lead to biased estimates of the correlation between worker and firm 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 visualize 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.[20]

An event is defined as the arrival of a HT manager to a unit previously managed by a 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 fast-food company, 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 fast-food 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 a LT to being managed by a HT manager.[21]

We estimate the following equation:

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

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; $D^k_{jt} = 1[t = \tau_j + k]$ 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 a HT manager to a unit previously under a LT manager significantly boosts training take-up (see Figure 3). For the car manufacturer and the retailer, the arrival of a HT manager increases training take-up both in the immediate eight weeks after the arrival and nine weeks or more after the arrival. For the car company, the arrival of a 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 fast-food company, 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

[20]For robustness, we also explore alternative definitions, including categorizing as HT those managers whose value added is above the 75th and 90th percentiles of the distribution. These different definition do not affect the results observed throughout the paper and are shown in Appendix.

[21]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.

manager.[22]

Figure 3: The arrival of a HT manager boosts training take-up

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

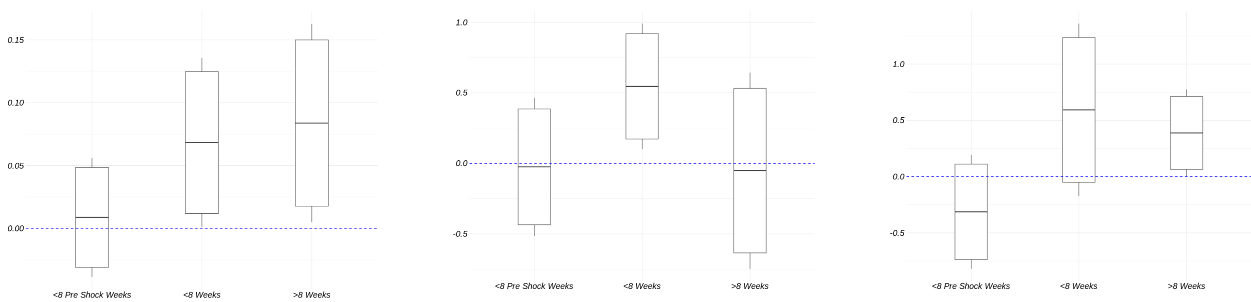


Figure 3 shows the percentage change in the training variable after the arrival of a HT manager in a store (panels b and c) or working group (panel a) previously under an LT manager, in the first eight weeks after the arrival and the effect after more than eight weeks. For the car company, the effect in the first eight weeks is 6.82%, and after eight weeks, it is 8.38%; for the fast food chain, the effect in the first eight weeks is 54.53%, and after eight weeks, it is -4.16%. Finally, for the retail company, the effect in the first eight weeks is 59.28%, and after eight weeks is 38.78%. 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.

4.3 What Characterizes HT Managers?

In this section, we explore the characteristics of HT managers. First, we examine whether HT managers specialize in specific types of training. Next, we study whether HT managers share a common profile in terms of age, gender, or tenure. Finally, we conduct a survey in the fast-food company to study possible differences in personality or leadership and management approaches.

Training programs HT managers may merely focus on shorter or simpler programs, allowing them to train a larger number of employees overall. To explore this possibility, we leverage detailed information on training and 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 fast-food 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

[22] 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 E.6 in the Appendix.

of training specialization. HT managers seem to train their supervised workers in all operational training types, regardless of the specific sub-type.

Figure 4: HT managers vs. specific trainings

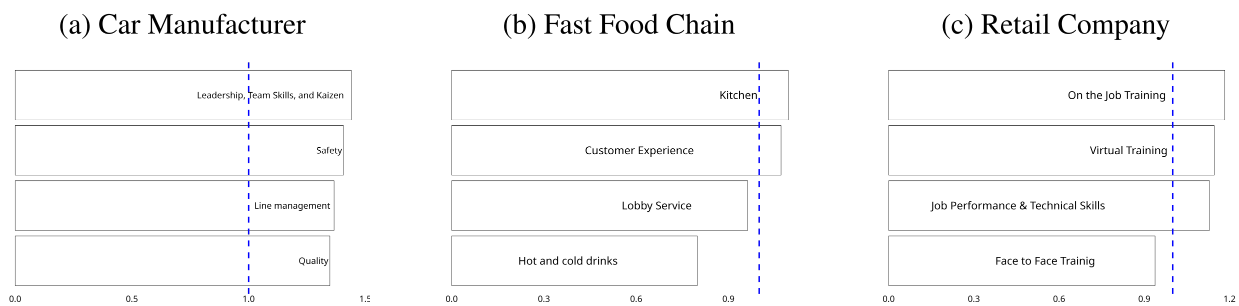


Figure 4 illustrates the ratio of trained employees managed by high-training (HT) managers to those managed by low-training (LT) managers, categorized by training type across the three companies. For the car manufacturer, we examine groups such as leadership, team skills and Kaizen, safety, line management, and quality training. In the fast food chain, the focus is on training categories including kitchen skills, 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.

Demographics We study whether certain demographic characteristics of the managers correlate with a manager training more workers.[23] 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 fast food chain and the retail company, though we see some difference in tenure for the retailer (HT managers are younger).[24] Thus, there is no evident manager demographic "profile" that is associated with training more workers.

For the fast food chain, we also test if HT managers are concentrated in particular shifts, that is, if HT managers mainly work during the day while LT managers take the night shift (or the other way around), or if HT managers work different hours than LT managers, since this may make it easier to encourage training. Figure E.7 shows no particular evidence of concentration of shifts. In other words, we find no evidence that either morning or night shift managers are more likely to be HT.

Management Practices and Leadership Style There is a substantial body of literature documenting the importance of management practices in organizations, demonstrating that structured management practices can significantly improve firm productivity (Adhvaryu et al., 2021, 2022; Bloom et al., 2014, 2012; Bloom and Van Reenen, 2010; Frederiksen et al., 2020; Friebel et al., 2023; Hoffman

[23] Understanding if a demographic profile might predict HT management is important because it can help organizations identify and develop effective training leaders, tailor training programs to fit these profiles and optimize the allocation of managerial resources.

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

Table 2: HT managers vs Demographics

	Fast food 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 ($\frac{Male}{Female}$)	0.603	0.661	0.254	0.631	0.706	0.188

Table 2 presents the differences between High-training (HT) and Low-training (LT) managers across various demographic variables, including age, tenure, and gender, for both fast food 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.

and Tadelis, 2021; Metcalfe et al., 2023). To explore whether HT managers differ in terms of leadership or management style, we conducted a large-scale management survey with middle managers in the fast-food company. We then matched the survey responses with the estimated fixed effects from our initial analysis (204 managers in total) to gain deeper insights into the characteristics and traits of HT managers.

We categorize our analysis and results into four main areas: individual managerial characteristics, outcomes and activities, operations, and human resources. The *individual characteristics* variables include education, gender, 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 measures help us understand how HT managers perceive themselves and their capabilities, as well as their cognitive and emotional intelligence. The *outcomes and activities* category examines the total productivity problems faced by the manager, the number of active operations they oversee, and their daily operational activities. It provides insights into the practical challenges and workload that managers handle. The *operations* category focuses on problem-solving and continuous improvement practices within the management framework. It includes problem-solving, identifying solutions to problems, management problem-solving, problem-solving for employees down the line, problem-solving for upper management, the number of KPIs, the frequency of KPI reviews, the frequency of retrospective learning, targets, and Kaizen practices.[25] Finally, the *human resources* category covers different personnel management practices, including planning employees, valuing friendliness as a skill, promoting based on KPIs, retaining star performers, talking to underperforming workers, providing feedback to employees, and assessing employee well-being and motivation frequently. It reflects HT managers' emphasis on employee well-being and motivation, their approach to performance management, and their

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

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 effects on each survey variable. The coefficients for each survey category are then plotted in the corresponding Figures 5 and 6. This shows that HT managers are distinct from others in some key dimensions. In the individual characteristics category presented in the left panel of Figure 5, 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 on, which we consider to be a proxy for overall effort.

Figure 5: Individual Characteristics and Outcomes and Activities vs Manager's Fixed Effects

(a) Individual Characteristics

(b) Outcomes and Activities

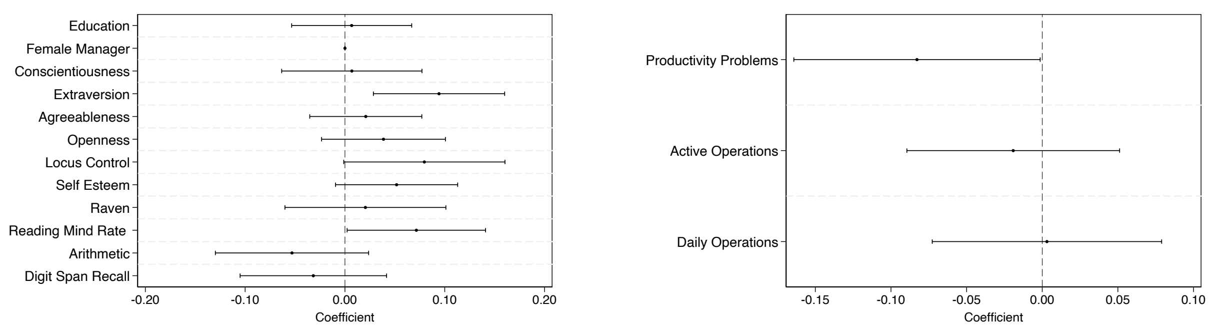


Figure 5 plots the coefficients from regressing the manager fixed effects on each survey variable score for each manager. The figure presents the coefficients from the main regression for individual characteristic as well as outcomes and activities variables for 204 managers that completed the survey. The survey was conducted in March 2023, achieving a 90% response rate.

Figure 6: Operations and Personnel Practices vs Manager's Fixed Effects

(a) Operations

(b) HR

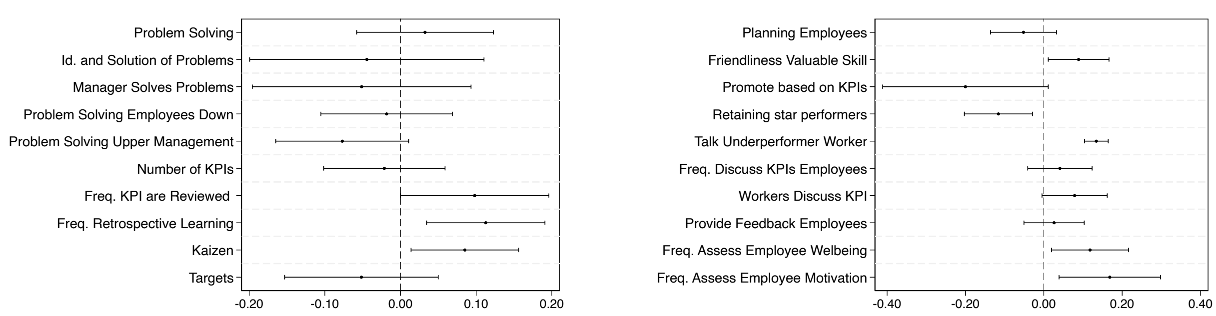


Figure 6 plots the coefficients from regressing the manager fixed effects on each survey variable score for each manager. The figure presents the coefficients from the main regression for Operations and Personnel practices for 204 managers. The survey was conducted in March 2023, achieving a 90% response rate.

While in many management practices HT managers are indistinguishable from LT managers, we found significant differences in some operations and personnel practices self-reported by the managers. 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 on the Keizen module of the survey, such as whether the manager received and implemented suggestions regarding operations from its team. Finally, the right panel 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. However, they are significantly less likely to focus their attention on top performers and superstar workers. Overall, these data suggest that HT managers tend to focus on the lower end of the employee performance distribution, and to be more focused on team dynamics relative to LT manager.

5 High Training Managers and Performance

A natural question to ask is whether HT managers are able to achieve greater performance than the others. Conceptually, this may not necessarily be the case. This is because training is a costly activity for managers, who trade off the loss of workers' time while they get trained, and of their own time too, since they need to expend effort in matching workers with training opportunities and certifying their skills after they train, in exchange for an increase in workers' productivity. Additionally, being a HT manager is correlated with other managerial activities that present similar trade-offs: as discussed in Section 4.3, HT managers are more likely to invest time engaging in problem solving and retrospective learning with workers, assessing workers' well being, and coaching underperformers, whereas LT managers are more likely to focus their attention retaining star performers. For a given managerial time constraint, and to the extent that HT and LT face similar tasks in production, they may achieve similar productivity levels with different combinations of managerial and workers' labor inputs, i.e. they may be horizontally (rather than vertically) differentiated.[26]

To provide *prima facie* evidence on this point, we re-estimate our AKM model using productivity (sales per employee) as the outcome variable for both the fast-food and retail companies over a time period characterized by relatively stable business conditions.[27] We then compare the fixed effects

[26] This is similar to what has been observed for CEOs (Bandiera et al., 2020). Also, recall managers are not directly compensated for training their workers, which may explain why LT and HT managers are both observed in equilibrium.

[27] By "stable," we meant before the demand shock, which is studied in the following subsections. This amounts to a duration of approximately 6 months for the fast-food chain and 18 months for the reatailer. Also, it is not possible to calculate the correlation between manager fixed effects and productivity for the car company because the productivity measures (defects per vehicle and total cars produced) are at the line level, not at the manager level.

from our AKM analysis of training take up to those from our analysis of productivity and plot the correlation between them. Figure 7 illustrates the results of this exercise. The correlation between the fixed effects is small: 0.121 for the fast-food company and 0.3 for the retail company. This shows some, but little differentiation in terms of productivity levels between HT and LT managers.

Figure 7: Correlation between Training and Productivity managers' Fixed Effects

(a) Fast Food Chain (b) Retail Company

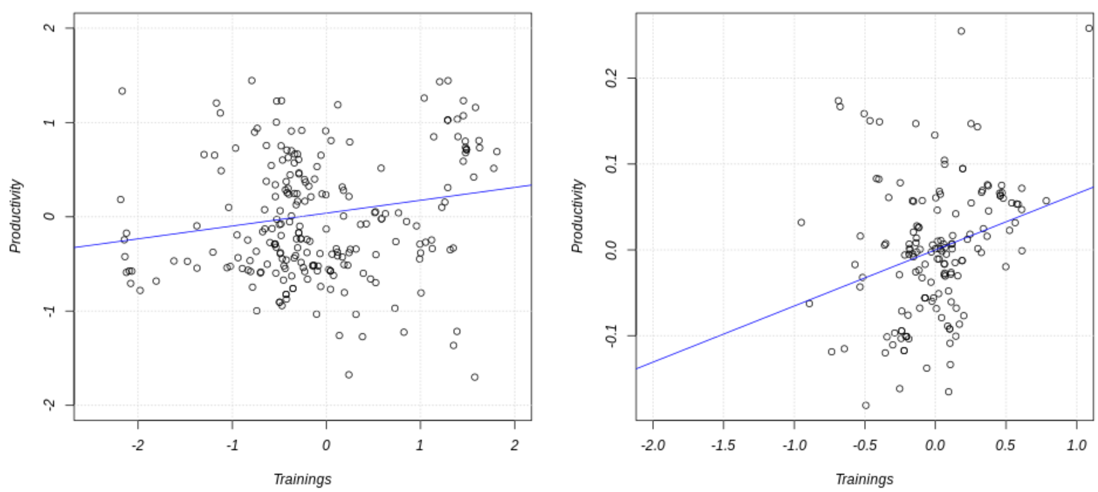


Figure 7 shows the correlation between training fixed effects and log productivity fixed effects for the fast food and retail companies, in the pre-shock period. For the fast food chain the correlation is 0.121, with a significance level of 0.068. For the retail company the correlation is 0.27, with a significance level of 0.001.

The effects of HT managers on performance, however, may be different when teams do not operate in stable business conditions, for instance when they face new circumstances in which training is valuable. This would be the case, for example, when workers need to be more efficient in their typical tasks, or need to learn new tasks (for example, if they need to engage with a different production process or a new technology, or if they have to exercise autonomous judgment more frequently).[28] To the extent that teams led by HT managers face a lower cost of engaging in training, this may translate in performance differentials across managers, at least in the immediate aftermath of the shock.[29] This suggests that the role of HT manager is contingent on the need for change and adaptation.

To study this hypothesis, we take advantage of the fact that for all three firms in our sample we observe a period of time in which all firms experienced a large and sudden positive demand shock

[28] Aghion et al. (2021) document that firms that were more decentralized–i.e. which relied on greater middle manager autonomy and judgement–prior to the Great Recession were able to better adapt to new business conditions, for example by better adapting their product offering to customers' needs.

[29] To the extent that conditions revert back to normal circumstances, or that LT managers can rapidly switch into becoming HT managers, these performance differentials may be erode as business goes back to normal.

that exogenously changed workload requirements, forcing teams to adapt to a new and more high-pressure work environment. For the auto company, there were two centrally mandated production expansions initiated by headquarters. The first expansion increased production by approximately 27%, and the second by about 38%. These expansions simultaneously affected all teams across the plant, heightening the need for efficiency and task management. For the fast food chain and retail company, it was the staggered roll-out of a partnership with a last-mile delivery service that increased overall sales by 6% and 3%, respectively, across all stores.

We study whether HT managers became more valuable in the immediate aftermath of these demand shocks. We consider as key outcomes both team production and a critical HR indicator, workers' absenteeism (Adhvaryu et al., 2024). The latter is of particular salience for the specific shocks we consider since, across all three firms, the exogenous mandate to increase production was not matched by an increase in personnel, greater wages and/or bonuses, or working hours. Therefore, the mandated increase in production effectively required workers to exert more effort per hour (i.e., perform more tasks per unit of time) without a commensurate increase in pay. Mapping the shock onto a simple labor supply model, the shock acted as an exogenous shift of workers' labor supply to an out-of-equilibrium point, where the marginal rate of substitution of leisure for consumption (MRS) is greater than the wage. To the extent that workers engage in absenteeism to reduce the wedge between the MRS and their wage (Dunn and Youngblood, 1986), we thus expect the demand shock to be followed by an increase in workers' absenteeism.[30]

Why would HT managers matter in this circumstance? Note that the effects of the shock on absenteeism depend on workers' MRS: specifically, a greater preference for leisure over work implies a stronger response to the shock. To the extent that training and/or adopting the practices discussed in Section 4.3 affect workers' preferences for work (i.e., they lower the MRS, and hence reduce the wedge between the MRS and the wage after the shock), then we expect that HT managers would see a smaller increase in absenteeism relative to LT managers after the demand shock.[31]

In what follows, we first study the effects of the demand shocks on direct and indirect team performance measures across all managers. We then examine the differential response to the demand shock across teams reporting to HT and LT managers. Third, we study the heterogeneity in the response to the shock of HT managers within teams across different hierarchical levels and occupations, and across teams.

[30] See Appendix D for a more detailed discussion of absenteeism as a response to return to an equilibrium where the MRS is equal to the wage.

[31] For example workers reporting to HT managers may be more productive thanks to training, or be exposed to better working conditions thanks to the other practices used by HT managers. Furthermore, other channels may be at play. For example, workers reporting to HT managers may be engaged in "gift exchange," i.e. provide greater effort without an improvement in skills and knowledge as in Akerlof (1984). Unfortunately, we are not able to distinguish between these alternative channels.

5.1 The Demand Shocks

As discussed above, for three companies we have access to performance data relative to a period characterized by a significant increase in demand.

For the car company, we examine two sudden increases in the total production of the plant requested by central headquarters. Specifically, central headquarters exogenously increased production targets to increase the total number of cars assembled in the plant. Both expansions can be thought as exogenous demand shocks that hit all working units within the plant with similar strength. The first shock occurred four months into the panel data since, and the second shock took place approximately 9 months into the panel. The production changes in both cases were implemented simultaneously across the plant for all working groups. To analyze the two shocks separately, we split the database, analyzing only a window of eight biweeks before and after each shock.

For both the fast-food and retail companies, the introduction of the delivery app service allowed consumers to order items delivered to their preferred location, thereby increasing transactions and sales: that is, this increase was not merely a substitution of in-person customers with online customers, but rather an expansion of the customer base and transaction volume for workers, which now had to manage both in-store and delivery orders. The rollout of the delivery app program was staggered, meaning that stores received the app at different times. 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. This setting allows for a staggered event study design.

5.2 Event Studies

We now turn to examining in more detail the value of HT managers in adapting to the demand shocks. To do so, our empirical analysis follows these steps. First, for each company, we estimate the effect of the demand shock on production or sales across the entire sample. Next, we study whether the effect of the shock was heterogeneous if the store or unit had an HT manager just (the month) before the shock hit the team. We classify stores with HT managers before the shock as HT management stores and those with LT managers as LT management stores.[32] We estimate the following regression,

[32] For stores with multiple managers, we categorize them based on the predominant manager type during the shock period (i.e., we take the mode).

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

where Y_{jt} is the performance of unit j in period t (pooled across 8 weeks) in terms of production and absenteeism; 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. To estimate the effect of an HT manager, 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. Finally, standard errors are clustered at the unit level.

Average Effects We begin by estimating the average effect of the demand shock on production for all units in the firms. Figure 8 shows that the demand shock increased production and sales both in the first 8 weeks immediately after the shock and beyond 8 weeks after the initial shock for the three companies. For the car company, the demand shock increased the number of cars produced at the factory level by around 25% in the immediate 8 weeks after the shock and by 39% after the initial 8 weeks on average. For the fast-food chain, the demand shock increased sales by close to 5% in the 8 weeks and afterward. Meanwhile, sales for the retail company increased by 2% in the immediate 8 weeks after the shock and around 4% afterward.

In all three companies, however, increase in production was accompanied by another change: a large increase in absenteeism, in line with the conceptual framework discussed above. Figure 9 shows that a spike in absenteeism is observed both immediately after the shock and after 8 weeks consistent with the duration of the demand shock (the shock remains throughout the period after it is initially observed). Following the shock, absenteeism increased by approximately 28% (after 8 weeks) for the car company and around 6-11% for both the retail company and the fast food chain.[33]

[33] We have 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. See tables E.9, E.8 for a robustness check in which we use the share of absent employees as a dependent variable (instead of the absolute number of absences).

Figure 8: Effect of the Demand Shock on Performance

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

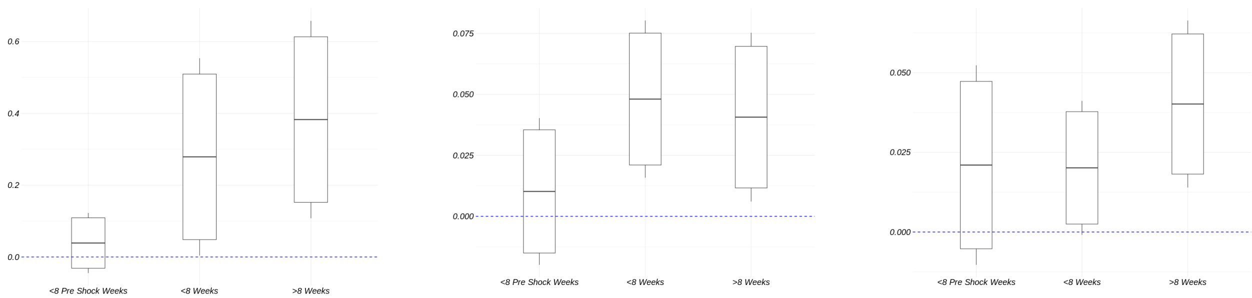


Figure 8, panel (a) shows the percentage change in cars produced for the car manufacturer after the shock. The effects are the average of the two shocks. Panel (b) and (c) show the effect of partnering with the last-mile delivery company on sales for each store in the first eight weeks and afterward. For the car company, the percentage change is around 27.88% for the first eight weeks and around 38.26% after eight weeks. For the fast food chain, the effect is around 5% for the first eight weeks and 4% after eight weeks. Finally, for the retail company, the effect is around 2% the first eight weeks and around 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

Figure 9: Effect of the Demand Shock on Absenteeism

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

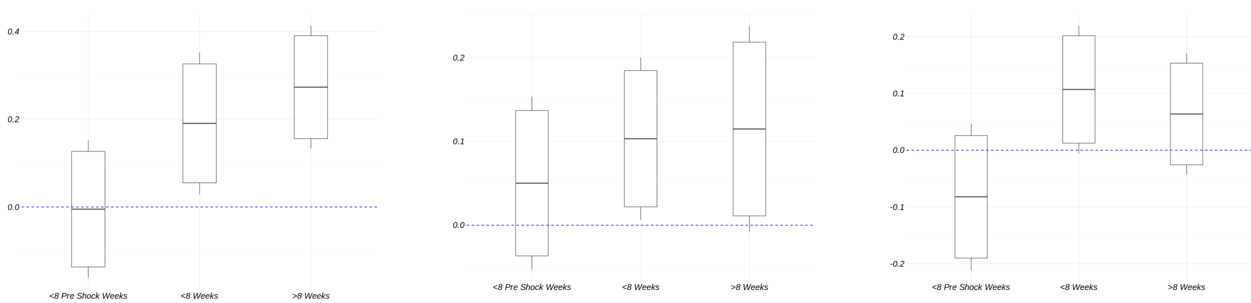


Figure 9 shows the percentage change in absent employees after the demand shock. For the car manufacturer, the effect for the first eight weeks is 19.06%, and after eight weeks, 27.30%. For the fast food chain, the effect for the first eight weeks is 10.81%, and after eight weeks, 11.25%. For the retail company, the effect for the first eight weeks 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

Heterogeneity across HT and LT Managers We now proceed to estimate equation (6) interacted with the HT manager dummy to compare the outcomes between HT and LT managers. Figure (10) summarizes these results.[34] When comparing HT and LT managers, we find that the increase in sales after the shock is slightly higher for HT managers. In the fast food chain, sales 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 sales, while the effect of the shock fades for stores with LT management. For the retail company, HT managers see higher sales 8 weeks after the shock, but the difference is not significant.

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

We find even starker differences when we focus on absenteeism, by estimating our main equation (6) interacting the relative time-to-treatment variables with the HT indicator variable. Figure 11 illustrates these results. HT managers see almost no change in absenteeism. For the car company, while LT managers see a 39% increase in absenteeism in the immediate 8 weeks after a shock, HT managers experience a decrease of 2% in absenteeism on average. Moreover, more than 8 weeks after the shock, LT managers see a 50% increase in absenteeism, while HT managers only see a 2% change on average. For the fast food 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.These results are significant at the 83% confidence interval.

Interestingly, the heterogeneous response to the shock is strictly related to the HT status of the manager. When we repeat the same analysis estimating 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 (using the productivity fixed effects estimated above during normal business conditions), we see very little difference in sales for the retail company, and *worse* results for the fast food 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 fast food 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 indicates that high-productivity managers are, if anything, similarly or less effective in mitigating absenteeism following a demand shock compared to their low-productivity counterparts.

In summary, HT managers appear to be able to increase production without a significant increases in absenteeism in the aftermath of the demand shocks. This supports the notion that a HT manager might not necessarily boost performance when tasks are routine, but when unexpected disruptions push workers out of equilibrium–and specifically when these shocks require them to exert more effort per hour. That is, the value of a HT manager appears to be contingent on the need for change and adaptation.

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

(a) Fast Food Chain (b) Retail Company

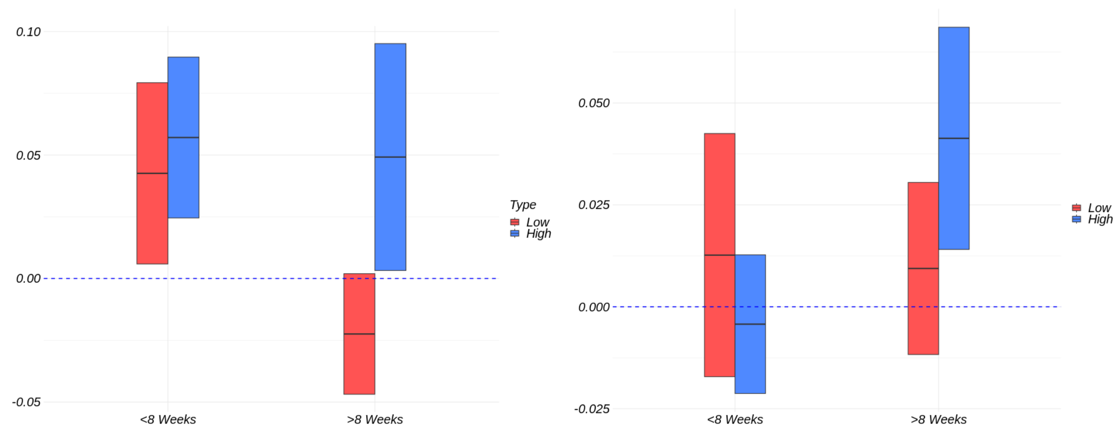
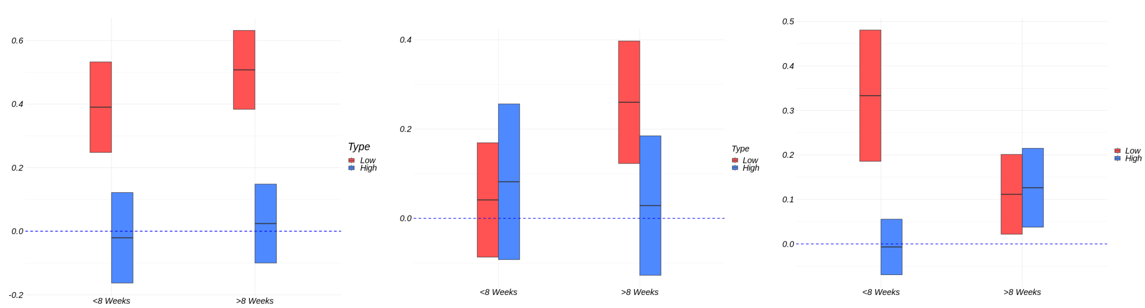


Figure 10 shows the percentage change in sales (fast food chain) and log transactions (retail company) in a store, eight weeks after the shock, and the effect after more than eight weeks. For the Fast food chain, the effect of the Low-training manager in the first eight weeks is 4.25%; after eight weeks, it is -2.24%, while the effect of the High-training manager in the first eight weeks is 5.70%; after eight weeks, it is 4.91%*. 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 0.93%, while the effect of the High-training 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%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

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



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure 11 shows the percentage change in absent employees in a working group (car company), and in a store (fast food 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 39.03%; after eight weeks, it is 50.76%, while the effect of the High-training manager in the first eight weeks is -2.05%*; after eight weeks, it is 2.43%*. For the Fast food chain, the effect of the Low-training manager in the first eight weeks is 4.12%; after eight weeks, it is 26.01%, while the effect of the High-training 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 Low-training manager in the first eight weeks is 33.33%; after eight weeks, it is 11.14%, while the effect of the High-training 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%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

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

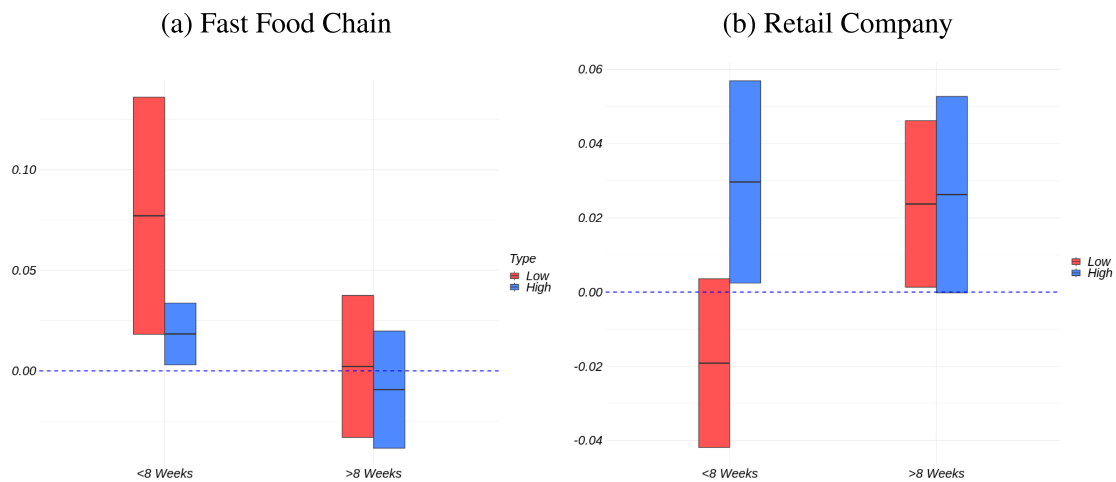


Figure 12 shows the percentage change in sales in a store, eight weeks after the shock, and the effect after more than eight weeks. Here we defined the High and Low productivity managers according to the productivity fixed effects. For the fast food chain, the effect of the low-productivity manager in the first eight weeks is 7.7%; after eight weeks, it is 0.2%, while the effect of the high-productivity manager in the first eight weeks is 1.83%; after eight weeks, it is -0.09%. Finally, for the retail company, the effect of the low-productivity manager in the first eight weeks 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%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

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

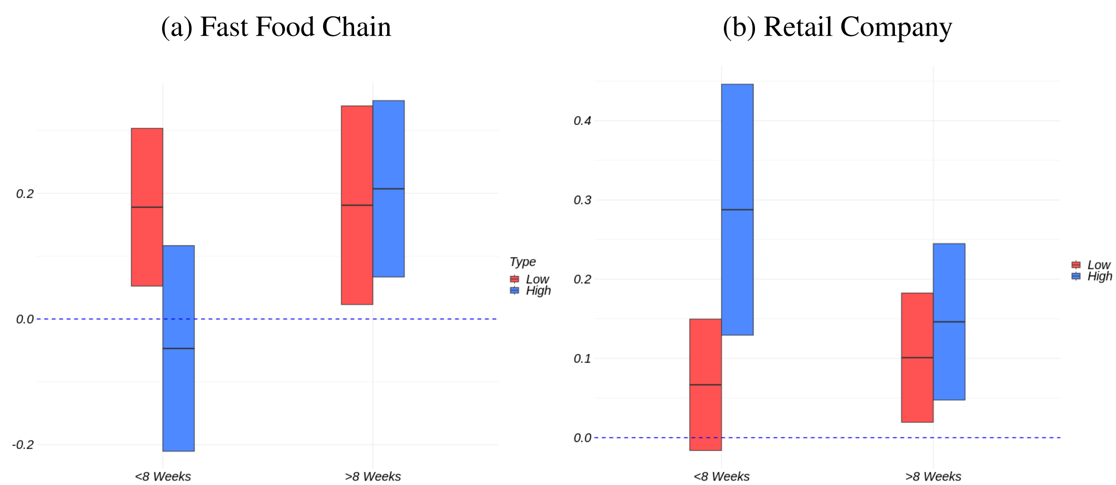


Figure 13 shows the percentage change in absenteeism in a store, eight weeks after the shock, and the effect after more than eight weeks. Here we defined the High-productivity managers with the productivity fixed effects. For the Fast food chain, the effect of the Low-productivity manager in the first eight weeks is 17.7%; after eight weeks, it is 18.10%, while 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%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

5.3 Additional Results

Robustness First, we explored the robustness of the results to different definitions of HT and LT managers using terciles instead of medians. Figure E.15 shows that high-training (top tercile) managers have higher productivity both in the immediate 8 weeks after the shock and beyond 8 weeks for the two companies. Likewise, Figure E.16 shows that managers in the top tercile consistently exhibit no effect on absenteeism in the immediate 8 weeks after the shock and beyond 8 weeks for the three companies. We discuss these results in more detail in Appedinx E.7.

Second, we studied 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 E.8 and E.9 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 E.9 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 fast food chain, and 35% for the retail company.

Presence vs. Exposure To study whether the effects of the shock depend on the actual presence and decisions of an HT manager during the shock, as opposed to the exposure to training that an HT manager may have provided prior to the shock, we estimated equation (6) on a subset of stores that experienced a managerial change from LT to HT just before the shock–i.e. focusing on stores that had HT managers only for relative brief periods. As shown in Figure 14, we see strong result on sales and absenteeism even in the subset of stores that were recently assigned an HT, suggesting that the effects depend on the presence of the HT manager during the shock.[35]

This interpretation is corroborated by the fact that HT managers appear to manage the shock quite differently from LT managers. First, estimating equation (6) with our measure of training as a dependent variable we see (Figure 15) that HT managers train more workers than LT managers while the shock occurs.[36] In the case of the car company, training usually implies removing workers from the production line, so it is costly for managers to train workers after the shock. In this case, we observe a lower reduction in the number of training take-up for HT than LT managers after the shock. In the fast food chain and retail company, HT managers continue to train their workers despite increased demand. Conversely, LT managers tend to reduce training in the 8-week period after the shock. Second, HT managers are also much more likely to promote workers during the shock [37] (car company) or maintain the number of promotions (as seen in the fast food and retail

[35] Unfortunately we cannot test this hypothesis for the car company since groups are constructed using the managers as the reference point.

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

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

Figure 14: Effect of Demand Shock on Absenteeism, by Manager Type (High and Low Training) for Newly Appointed Managers)

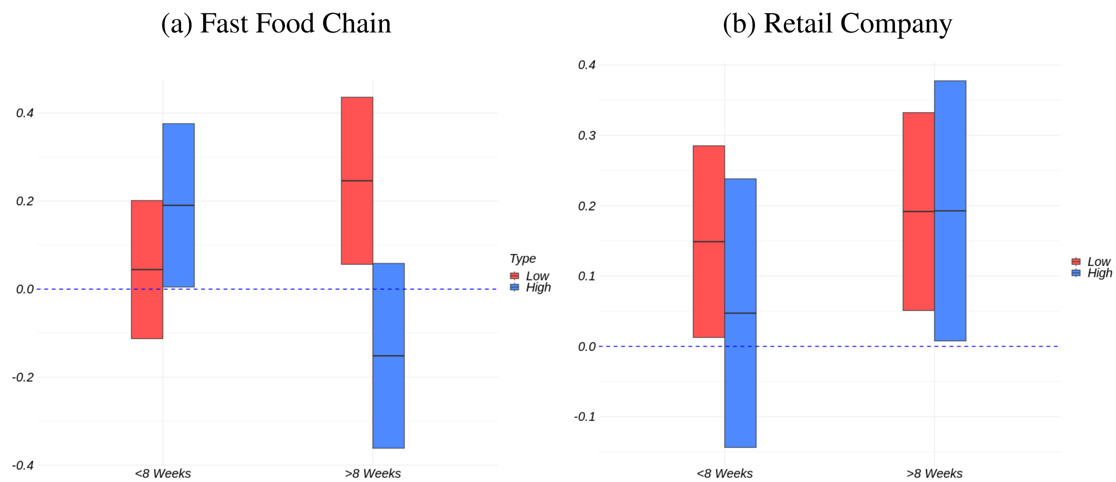


Figure 14 shows the percentage change in absent employees in a store for the fast food chain and retail company eight weeks after the shock and the effect after more than eight weeks. The analysis is done in stores where the period before the shock, didn't have a HT manager prior to the shock, but only afterwards. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 4.35%; after eight weeks, it is 25.32%, while the effect of the High-training 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 Low-training manager in the first eight weeks is 15%; after eight weeks, it is 19%, while the effect of the High-training manager in the first eight weeks is 3.41%; after eight weeks, it is 19.5%. We compare the coefficients of both types of managers at an interval confidence of 83%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

companies). Regarding promotions as shown in Figure 16, we find that in the car company, HT managers experience a steady increase, with a 41.82% rise in the first eight weeks and 50.29% afterward. In contrast, LT managers see an 8.95% increase in the first eight weeks and 26.86% afterward. In the fast food company, HT managers see a promotion increase of 5%, whereas we find no significant effect on promotions in the retail company. Overall, this evidence suggests that HT managers behave differently while the shock occurs.

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

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

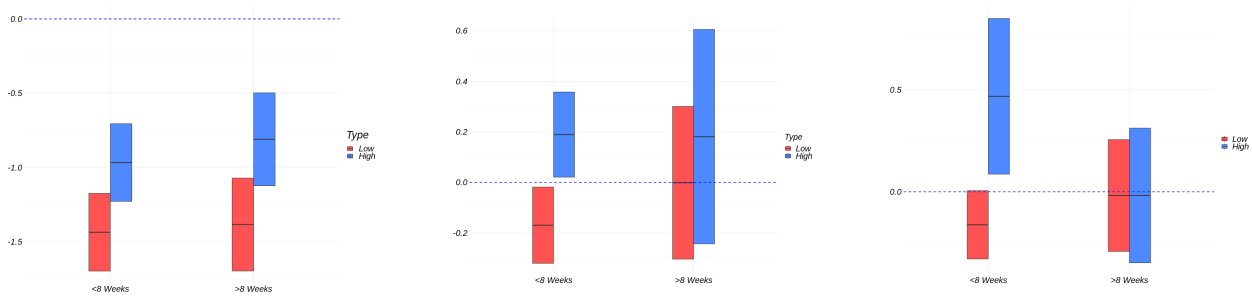


Figure 15 shows the percentage change in total training done by the employees in a working group (car company), and in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. For the car company, the Low-training manager effect in the first eight weeks is -132.27%; after eight weeks, it is -131.67%, while the effect of the High-training manager in the first eight weeks is -84.95%**; after eight weeks, it is -84.57%**. For the fast food chain, the effect of the Low-training manager in the first eight weeks is -18%; after eight weeks, it is 0%, while the effect of the High-training manager in the first eight weeks is 19%*; after eight weeks, it is 18%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is -16.22%; after eight weeks, it is -1.83%, while the effect of the High-training 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%. %. The * indicates 5% of significance level, while ** indicates 10% of significance level.

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

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

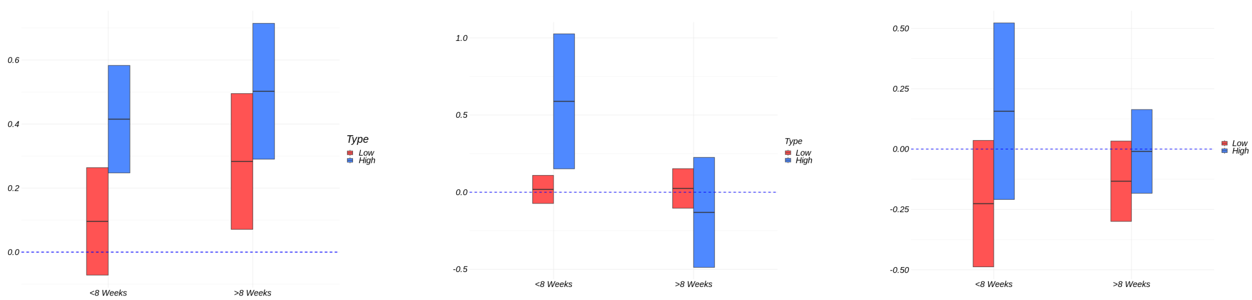


Figure 16 shows the percentage change in promoted employees in a working group (car company), and in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. For the car company, the Low-training manager effect in the first eight weeks is 8.35%; after eight weeks, it is 26.86%, while the effect of the High-training manager in the first eight weeks is 41.82%**; after eight weeks, it is 50.29%. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 5%; after eight weeks, it is 8%, while the effect of the High-training manager in the first eight weeks is 55%*; after eight weeks, it is -15%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is -22.59%; after eight weeks, it is -13.30%, while the effect of the High-training 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%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

6 Heterogeneity

We now turn to investigating 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.

6.1 Heterogeneity within Teams

6.1.1 Training Status

We start by studying the extent to which the absenteeism response varied across different types of employees. In particular, in Appendix E.7.5, we examined differences between employees that had already received significant training vs. those that were relatively less skilled prior to the shock (which we define as above and below the median of cumulative training before the demand shock). Figure E.19 shows no significant impact of the demand shock on absenteeism for high-trained employees, whereas we see a strong increase in absenteeism among low-trained employees (Figure E.20). Figure E.21 shows that this is exactly the type of workers for which HT managers matter the most.

6.1.2 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.[38]

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

Our findings indicate that the effects of the shock on absenteeism are more pronounced at lower levels of the firm hierarchy. Figure 17 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.

Figure 17: Effect of the Demand Shock on Absenteeism, by Hierarchical Level

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

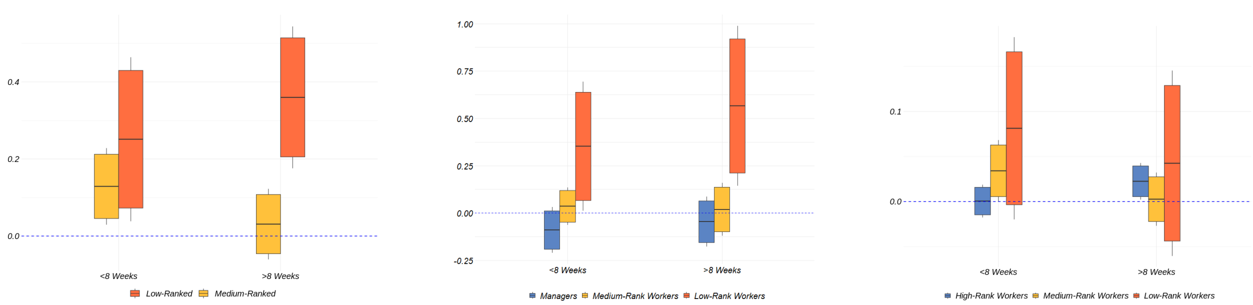


Figure 17 shows the percentage change in absent employees by hierarchal level for each company. We analyze low and managers employees for the car company, while for the fast food chain and retail company we analyze low-rank employees, medium-rank employees and managers. The analysis is done in the first eight weeks after the shock and the effect after more than eight weeks. 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%, while the effect for the managers in the first eight weeks is 12.89%; after eight weeks, it is 3.10%. For the fast food chain, the effect for the low rank employees in the first eight weeks is 35.3%; after eight weeks, it is 56.6%, while 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 8.13%; after eight weeks, it is 4.25%, while the effect for the medium rank employees in the first eight weeks is 3.41%; after eight weeks, it is 0.27%; finally, for the managers the effect in the first eight weeks is 0.06%; after eight weeks, it is 2.25%. We compare the coefficients of the types of managers at an interval confidence of 83%.

Figure 18: Effect of the Demand Shock on Absenteeism, by Manager Type (High and Low Training) for Lower Hierarchical Levels

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

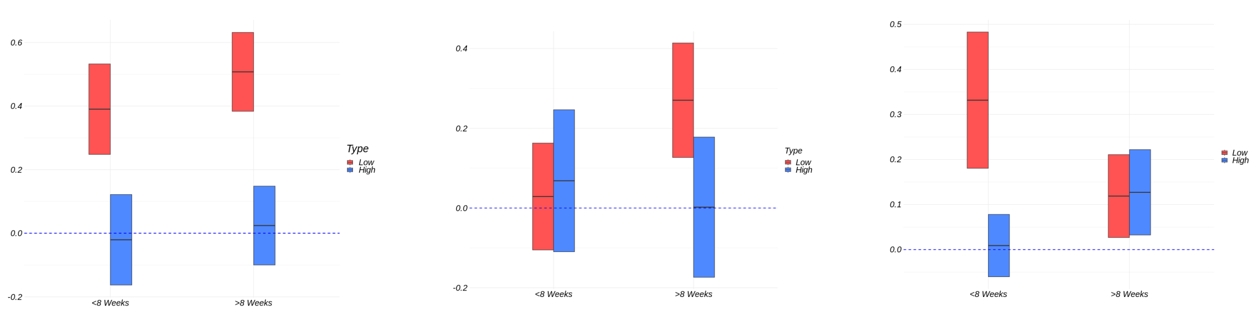


Figure 18 shows the percentage change in absenteeism for the low-ranked employees for each company. The analysis is done in eight weeks after the shock, and the effect after more than eight weeks. For the car manufacturer, the effect of the Low-training manager in the first eight weeks is 39.02%; after eight weeks, it is 50.75%, while the effect of the High-training manager in the first eight weeks is -2.05%*; after eight weeks, it is 2.43%*. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 3%; after eight weeks, it is 27%, while 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 * indicates 5% of significance level, while ** indicates 10% of significance level.

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 18 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.

6.1.3 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.[39] 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 fast-food company, 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 tickets 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 19 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 fast-food company, and cashiers in the retail company. We observe a direct and positive relationship between exposure to the shock and absenteeism.[40] Figure 20 shows that the impact of HT managers is particularly significant in these high-exposure 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.

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

[40] 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.

Figure 19: Effect of the Demand Shock on Absenteeism, by Occupation

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

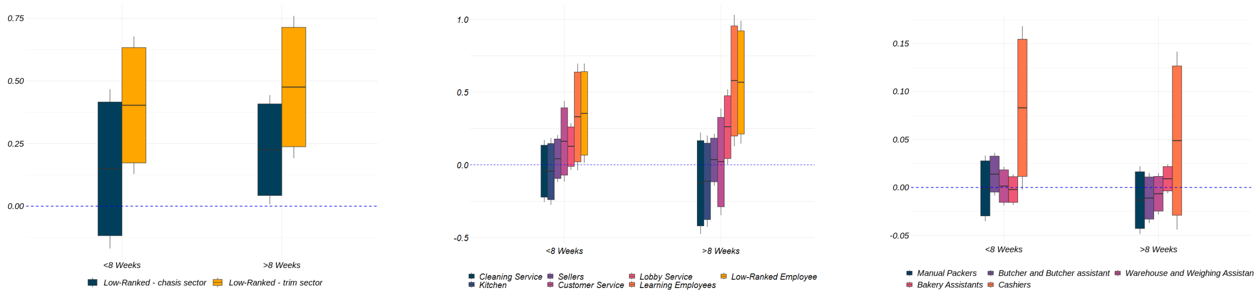


Figure 19 shows the percentage change in absent employees by horizontal hierarchy for the low-ranked employees in each company. We analyze the chassis and trim sectors for the car company, for the fast food chain we analyze the employees that are part of the following groups: cleaning, lobby and customer service, kitchen, sellers and apprentices; finally, for the retail company we analyze the employees that are part of: manual packers, butcher and butcher assistants, bakery assistants, warehouse and cashiers. The analysis is done in the first eight weeks after the shock and the effect after more than eight weeks. 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 effect for the trim sector in the first eight weeks is 40.30%; after eight weeks, it is 47.58%. For the fast food chain, the effect for 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%.

Figure 20: 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) Fast Food: Apprentices (c) Retail Company: Cashiers

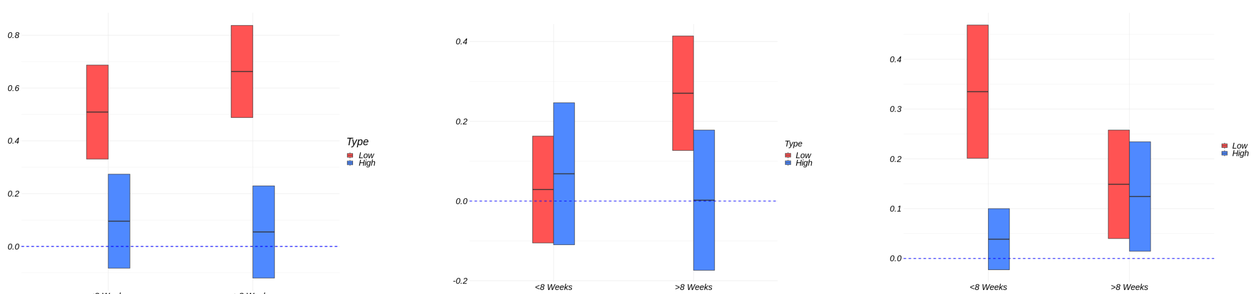


Figure 20 shows the percentage change in absenteeism for: sector trim for the car company, apprentices for the fast food chain and cashier employees for the retail company. The analysis is done in eight weeks after the shock, and the effect after more than eight weeks. For the sector trim employees, 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 * indicates 5% of significance level, while ** indicates 10% of significance level.

6.2 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.[41] 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.[42] We plot the results of the event study design for the two groups in Figure 21.

We observe that the rise in absenteeism after the demand shock is more pronounced in areas with low unemployment for both the fast-food chain and retail company. Specifically, in both companies, absenteeism increases significantly in the immediate 8 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 22 shows that HT managers experience a lower increase in absenteeism compared to LT managers in low-unemployment states.

7 Another Shock: Extreme Rainfall

As a final exercise, we study the response to a different type of ”shock”: extreme rainfall. Similar to Bandiera et al. (2018), we use rainfall as a proxy for increased cost of effort. Extreme rainfall significantly increases the effort required for employees to attend work, potentially having a similar effect to a demand shock. In this section, we examine how workers with HT managers react to rainfall shocks.

We impute rainfall in millimeters using data from the nearest weather towers to each city within a 50 km radius.[43] 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.[44]

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

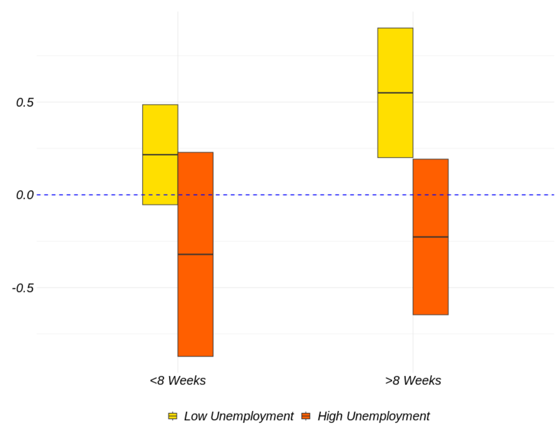
[42] These groups (i.e., high and low unemployment rates) are the same for the fast food chain and the retail company

[43] 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.

[44] We exclude the car company from this exercise, given that all working groups are located in the same assembly

Figure 21: The Effect of the Demand Shock in Low and High Unemployment States

(a) Fast Food Chain



(b) Retail Company

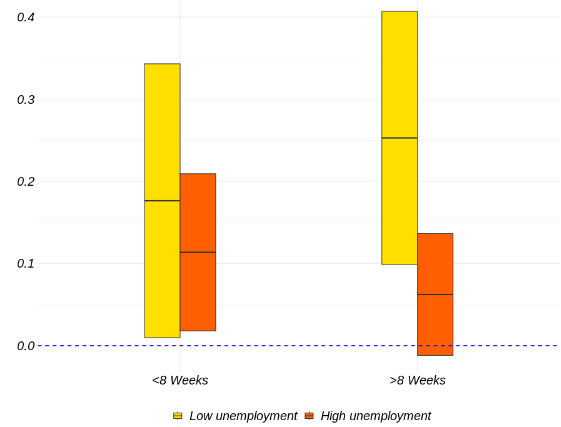
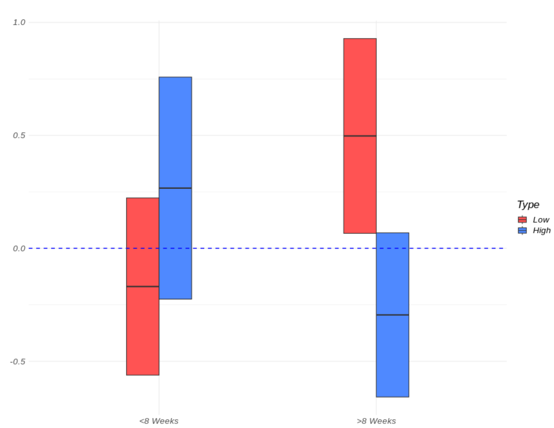


Figure 21 shows the percentage change in absenteeism in Low and High unemployment areas–i.e. we exploit differences in the competitiveness of labor markets–for the fast food chain and retail company stores in eight weeks after the shock, and the effect after more than eight weeks. To classify the areas, we compare the unemployment rate for each area to the national median of this variable. For the fast food 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 19.22 %; after eight weeks, it is 25.68%, while the effect in the high unemployment in the first eight weeks is 12.95 %; after eight weeks, it is 6.41%**. We compare the coefficients of both types of employment areas at an interval confidence of 83%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

Figure 22: The Effect of the Demand Shock by Manager Type (High and Low Training) in Low Unemployment States

(a) Fast Food Chain



(b) Retail Company

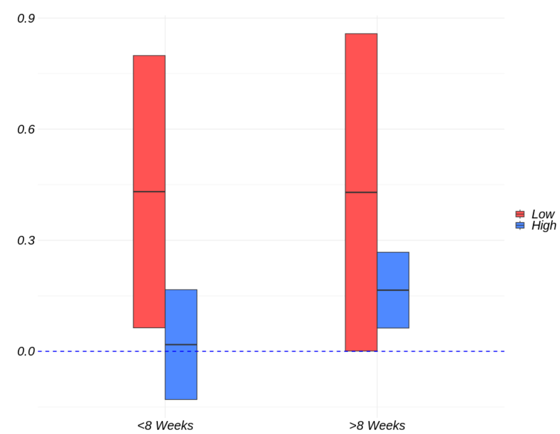
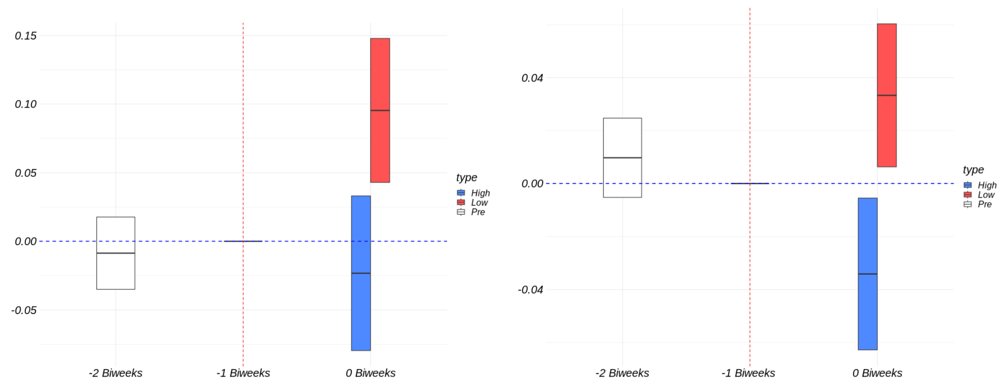


Figure 22 shows the percentage change in absenteeism in Low-unemployment areas for stores managed by HT and LT managers eight weeks after the shock, and more than eight weeks after the shock. For the fast food chain, the effect of the shock for LT managers in the first eight weeks is -21.64%; after eight 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 LT managers in the first eight weeks is 43.12%; after eight weeks, it is 42.94%, while the effect for the HT 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 at an interval confidence of 83%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

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 23, where we plot the percentage change in absenteeism in a store after a rainfall shock eight weeks after the shock and beyond for the fast-food 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 by 9.8% in the fast-food 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 23: Effect on Rainfall Shock on Absenteeism by Manager Type (High and Low Training)



(a) Fast Food Chain

(b) Retail Company

Figure 23 shows the percentage change in absent employees in a store for the fast food chain and retail company two weeks after the rainfall shock. For the fast food chain, the effect of the low-training manager in the two weeks is 9.8%, while the effect of the high-training manager in the two weeks is -2.5%*. Finally, for the retail company, the effect of the low-training manager in the two weeks is 3.33%, while the effect of the high-training manager in the two weeks is -3.4%*. We compare the coefficients of both types of managers at an interval confidence of 83%. The * indicates 5% of significance level, while ** indicates 10% of significance level.

8 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 fast-food chain, and a retail company in Latin America, we show that middle managers have a substantial impact on training participation rates among employees. Our findings demonstrate that teams led by high-training (HT) managers experience better engagement and lower absenteeism, particularly during periods of increased workload demands. HT managers are distinct in their focus on team development and employee engagement, compared to low-training

unit, resulting in no geographical variation.

(LT) managers who emphasize individual high performers.

These insights highlight the importance of middle managers in translating central HR policies into effective on-the-ground practices. 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. Future research should continue to explore the long-term impacts of middle managerial practices on firm productivity and employee career advancement.

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ONLINE APPENDIX

A Institutional Details

A.1 Role of Middle Managers

Car Manufacturer 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.

Fast-food 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.2 Training

Car Manufacturer Most new employees start as frontline (FL) workers, and they are onboarded to get basic skills required for entry-level positions.[45] Workers are promoted as they gain experience, complete specific training programs, and develop new job skills necessary for each layer of advancement. 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.

Fast-food 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 their practice in those areas. 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.

[45] E.g., basic production skills.

B Robustness of the AKM model

Sorting on training or productivity We begin by conducting an event study around moves to determine whether these moves are systematically driven by sorting on the match-specific component of training. Specifically, 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 E.2 plots the average biweekly residual training takeup of the movers on the y-axis.[46] 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 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 E.2.[47]

Figure E.4, 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 E.2. 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.[48] 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 E.4 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.

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

[47] 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.

[48] 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.

To test for endogenous mobility based on productivity, we conduct a similar analysis to that in Appendix E.2, using log(sales/number of employees) as the variable of interest. Figure E.3 presents similar characteristics to our training analysis, suggesting a symmetric relationship with respect to productivity. Similar to our symmetry test for training (Figure E.4), 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 Appendix E.5.

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 E.2 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 their subsequent moves to higher or lower training stores.[49]

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 fast-food company 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 fast-food 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

[49]The productivity analysis yields consistent results. There is no evidence of systematic pretrends in productivity prior to the move. Figure Appendix **??** demonstrates that the retail company does not exhibit any clear pretrends for any of the movements. Conversely, the fast food sector shows some pretrends before the move; however, these do not appear to be systematic.

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 fast food 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 E.2. Table E.2 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.[50] Despite slight differences in the covariance measure that show an existing but small bias in the direction that E.2 anticipates, the main results are largely robust across all correction methods implemented.

C Survey (In progress)

D Demand Shock and Absenteeism (In progress)

To study how the demand shock may have increased workers' propensity to engage in absenteeism, consider a simple labor supply model in which, in equilibrium, a worker's marginal rate of substitution between leisure and consumption equals their wage.

The demand shocks experienced by the three firms, requiring workers to exert more effort per hour without a commensurate increase in pay and without new hires, effectively increased workers' labor supply to an out of equilibrium point where the marginal rate of substitution is lower than their total wage. That is, the demand shock created a wedge between the marginal rate of substitution and the wage.

Following Dunn and Youngblood (1986), we posit that engaging in absenteeism is one of the ways through which workers adjust their labor supply to reduce the wedge, i.e. reducing their effort and working hours to return to equilibrium. This is consistent with the result that the demand shock was followed by a significant and large increase in absenteeism.

To see why HT and LT managers may have experienced a different increase in absenteeism after the demand shock, we map onto this simple model managerial heterogeneity leveraging the

[50]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 fast food chain and retail company datasets.

results emerging from the survey discussed in Section 4. These data show that HT managers are significantly more likely to invest effort in activities that improve workers' engagement and well-being. These differences are consistent with the idea that HT reduce workers' MRS. This, in turn, would imply that the absenteeism response to the same demand shock would be smaller for teams reporting to HT managers, since the wedge between the MRS and the wage created by the demand shock would be smaller for people managed by HTs.

E Appendix Figures and Tables

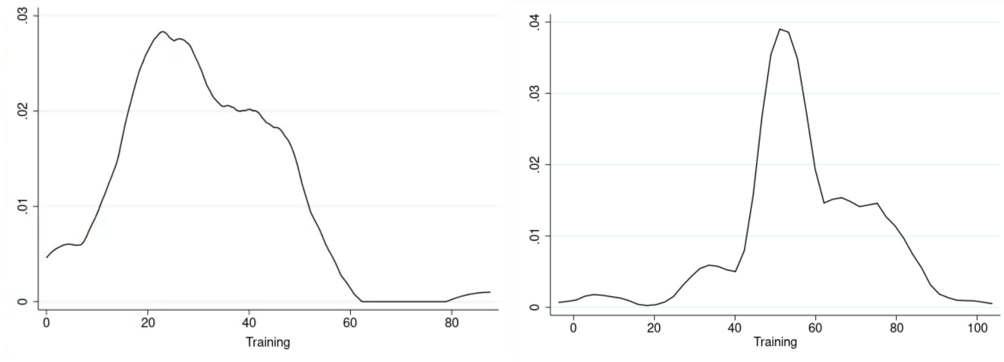
E.1 Organization of Production

Table E.1: Organization of production

	Car manufacturer	**Fast food chain**	**Retailer**
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.	Mass 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)	83 stores	83 stores
Number of managers	196	492	277

E.2 Store Fixed Effects Distribution

Figure E.1: Store Fixed Effects Distribution

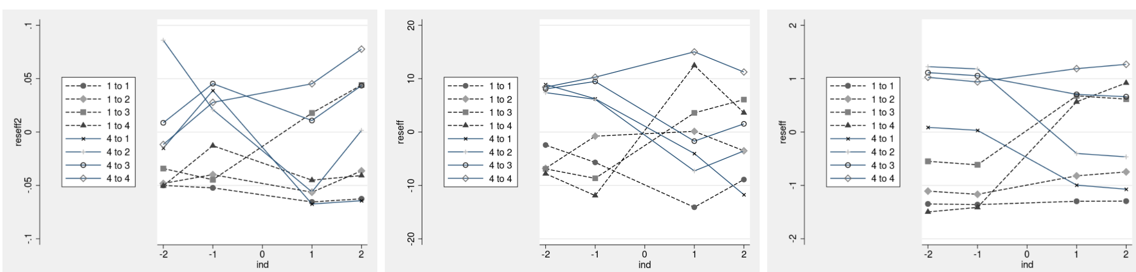


(a) Fast Food Chain (b) Retail Company

This Figure shows the store fixed effects distribution for the fast food and Retail companies, when we use as an outcome the training take-up. 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.

E.3 AKM Robustness Checks

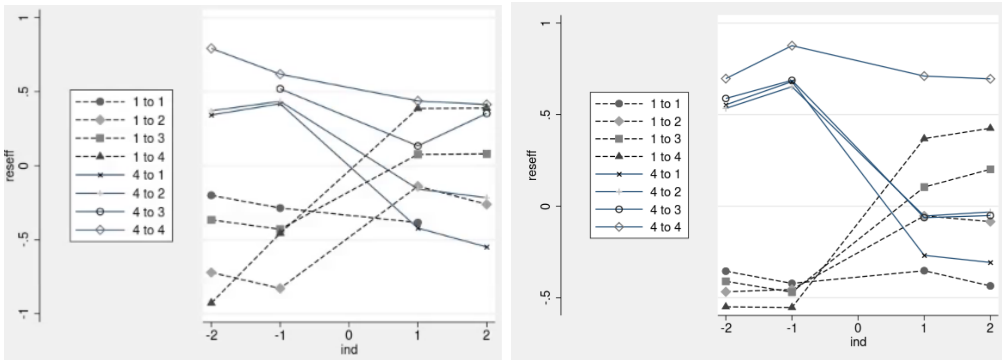
Figure E.2: Event Study Around Movers - Training



(a) Car Manufacturer (b) Fast Food (c) Retail Company

Figure E.2 assesses movers based on (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 graphical representation depicts the average residual training (reseff) of movers on the y-axis; the residual is computed 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 training of each working group (car company) and store (fast food and retail companies) on year and biweek fixed effects. Then we predict the residuals and run the movers analysis.

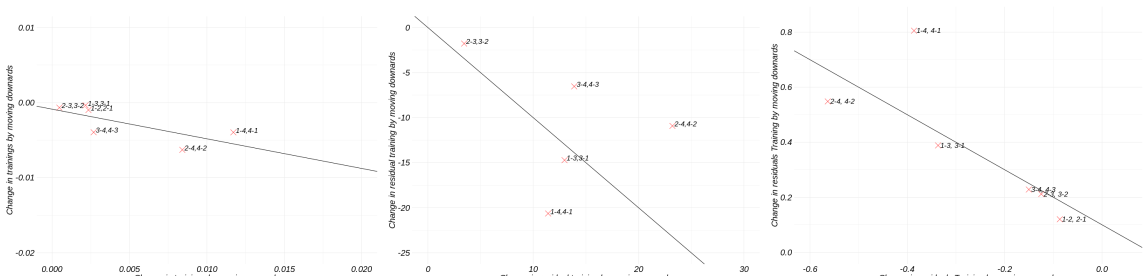
Figure E.3: Event Study Around Movers - log(Productivity)



(a) Fast Food Chain (b) Retail Company

Figure E.3 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 graphical representation depicts the average residual productivity (reseff) of movers on the y-axis; the residual is computed 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.

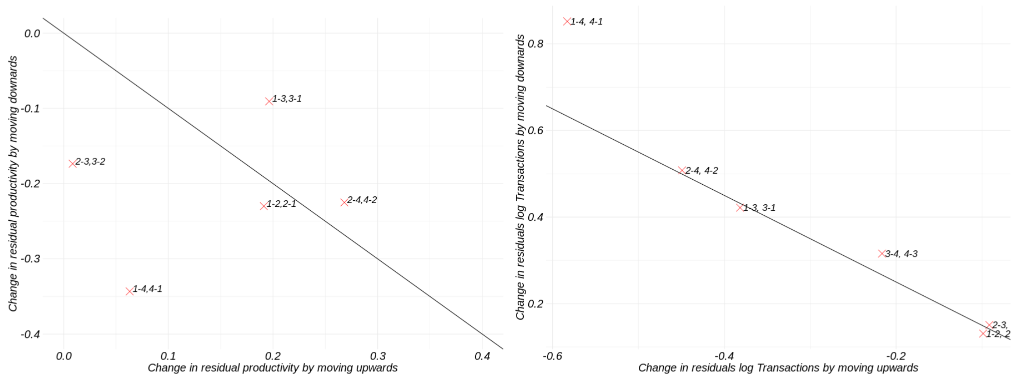
Figure E.4: Symmetry Test - Training



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.4 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 8 weeks before the move and the 8 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 (fast food and retail companies) each biweek, on year and biweekly fixed effects. Then, we predict the residuals and run the movers analysis.

Figure E.5: Fast Food and Retail Company: Symmetry Test - log(Productivity)



(a) Fast Food Chain (b) Retail Company

Figure **??** 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 8 weeks before the move and the 8 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.

E.4 Limited Mobility

Table E.2: 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
		Fast Food 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
		Retailer	
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

Table E.2 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 fast food chain, the analysis is done between June 2018 and November 2019 for 83 stores. Finally, the study for the retailer company is conducted for 64 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 (fast food 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 between all the models.

E.5 Portability Results using split samples

Figure E.6: The arrival of a HT manager boosts training take-up

(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

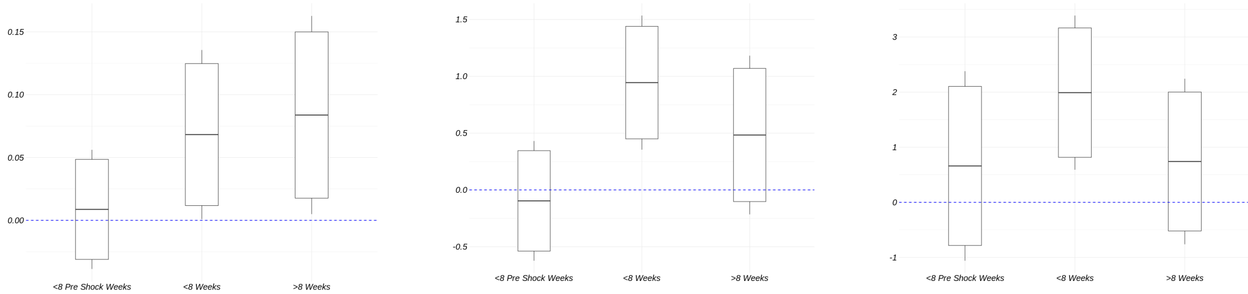


Figure E.6 shows the percentage change in the training variable after the arrival of a high-training manager defined in the pre-shock sample, in low-training management in a working group for the panel (a) and store for the panels (b) and (c) in the aftershock sample; in the first eight weeks after the arrival and the effect after more than eight weeks. For the car company, the effect in the first eight weeks is 6.82%, and after eight weeks, it is 8.38%; for the fast food 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 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.

E.6 Shifts by Manager Type

Figure E.7: Shifts by Manager Type

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

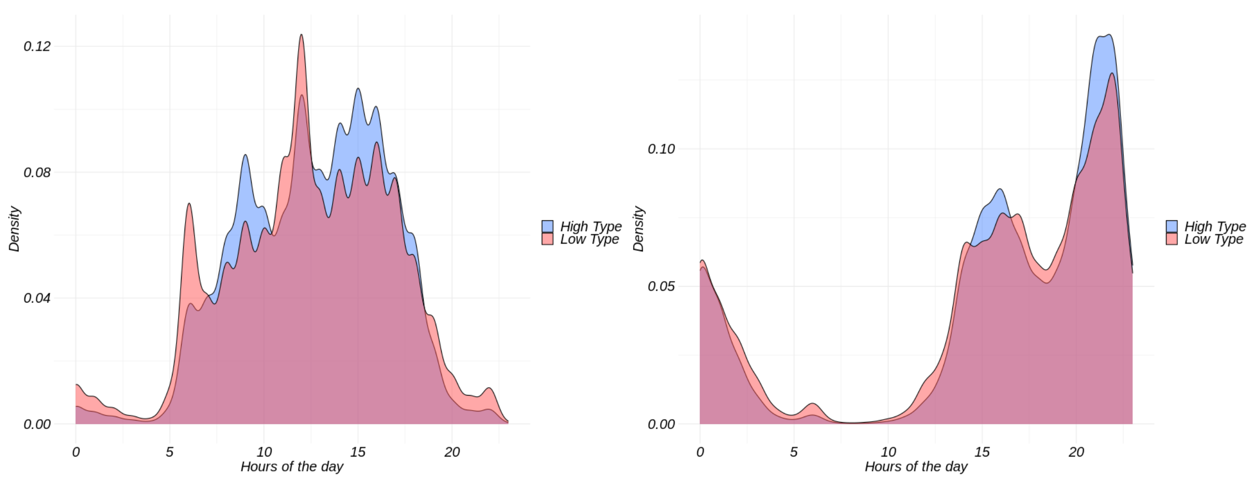
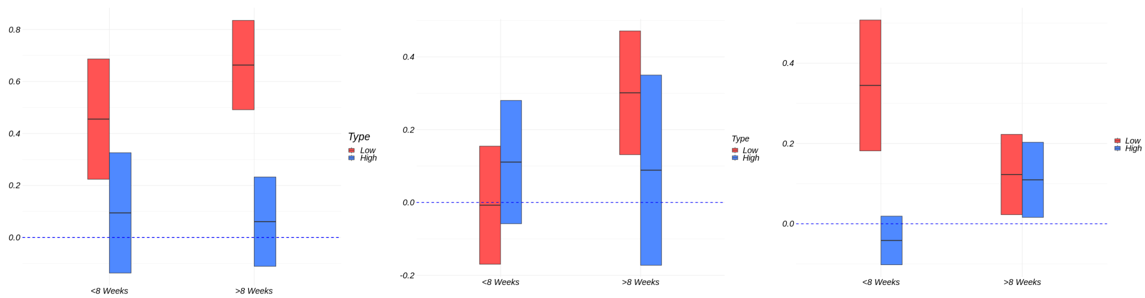


Figure E.7 plots the density graph of the High-Training and Low-Training managers' arrival and hours to leave work between 00:00 and 24:59 hours for the **fast food chain**. There is no significant difference between both types of managers in terms of shifts.

E.7 Additional Results for the Demand Shock

E.7.1 Different definitions of Absenteeism

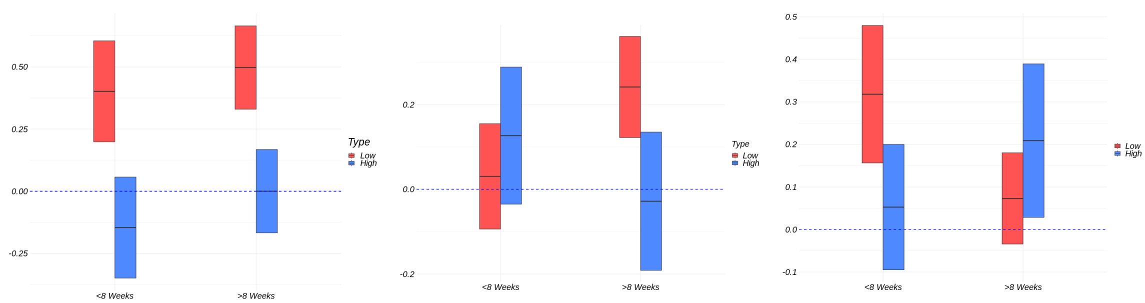
Figure E.8: Effect of Demand Shock on Total Absences, by Manager Type



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.10 shows the percentage change in total absents in a working group (car company), and in a store (fast food 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 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 fast food 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 7.30%, 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%.

Figure E.9: Effect of Demand Shock on Share of Absent Employees, by Manager Type

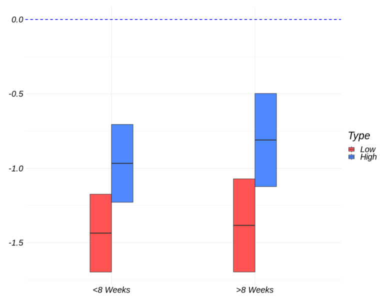


(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

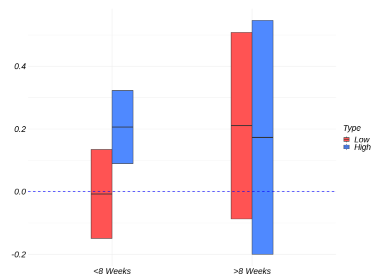
Figure E.10 shows the percentage change in share absent employees in a working group (car company), and in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. For the car company, the Low-training manager effect in the first eight weeks is 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 fast food 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%.

E.7.2 Effect of Demand Shock on Training and Promotions for all the Workers

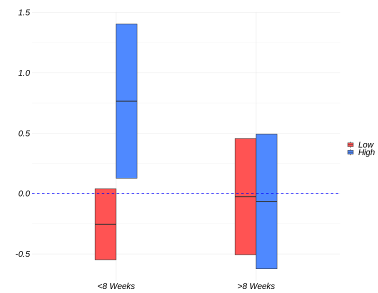
Figure E.10: Effect of Demand Shock on Training, by Manager Type



(a) Car Manufacturer



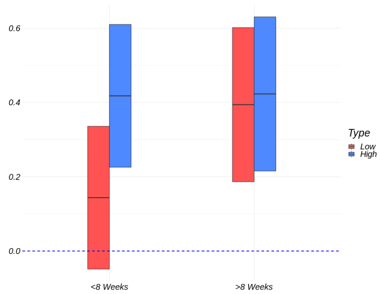
(b) Fast Food Chain



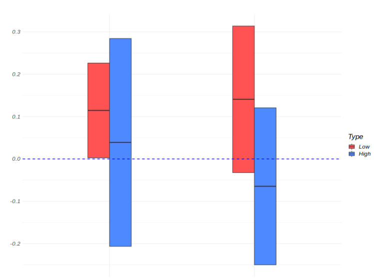
(c) Retail Company

Figure E.10 shows the percentage change in total training in a working group (car company), and in a store (fast food 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 -132.27%; after eight weeks, it is -131.67%, while the effect of the High-training manager in the first eight weeks is -84.94%; after eight weeks, it is -84.57%. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 0%; after eight weeks, it is 22%, while the effect of the High-training manager in the first eight weeks is 21.05%; after eight weeks, it is 17.32%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is -25.38%; after eight weeks, it is -2.51%, while the effect of the High-training manager in the first eight weeks is 76.52%; after eight weeks, it is -6.48%. We compare the coefficients of both types of managers at an interval confidence of 83%.

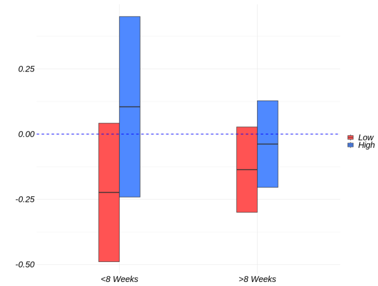
Figure E.11: Effect of Demand Shock on Promotion, by Manager Type



(a) Car Manufacturer



(b) Fast Food Chain

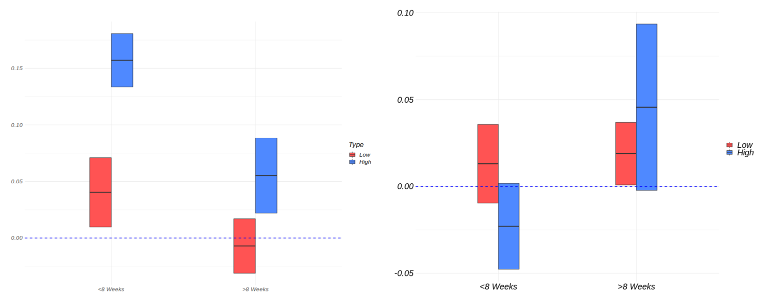


(c) Retail Company

Figure E.11 shows the percentage change in total promotions in a working group (car company), and in a store (fast food 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 14.37%; after eight weeks, it is 39.43%, while the effect of the High-training manager in the first eight weeks is 41.78%; after eight weeks, it is 42.29%. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 12%; after eight weeks, it is 14%, while the effect of the High-training manager in the first eight weeks is 4%; after eight weeks, it is -7%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is -22.36%; after eight weeks, it is -13.62%, while the effect of the High-training manager in the first eight weeks is 10.46%; after eight weeks, it is -3.81%. We compare the coefficients of both types of managers at an interval confidence of 83%.

E.7.3 Analysis for the 75th Percentile

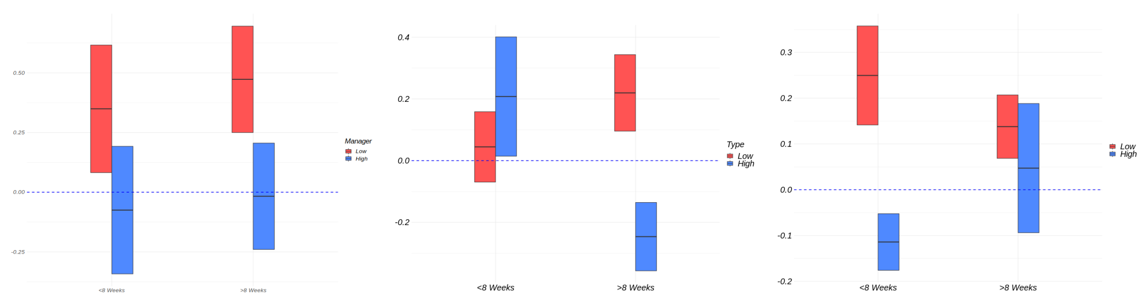
Figure E.12: Effect of Demand Shock on Sales, by Manager Type (HT - 75th Percentile)



(a) Fast Food Chain (b) Retail Company

Figure E.12 shows the percentage change in total sales in a store (fast food and Retail companies), eight weeks after the shock, and the effect after more than eight weeks. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 4.25%; after eight weeks, it is -2.2%, while the effect of the High-training manager in the first eight weeks is 16.5%; after eight weeks, it is 5.91%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is 1.31%; after eight weeks, it is 1.89%, while the effect of the High-training manager in the first eight weeks is -2.29%; after eight weeks, it is 4.56%. We compare the coefficients of both types of managers at an interval confidence of 83%.

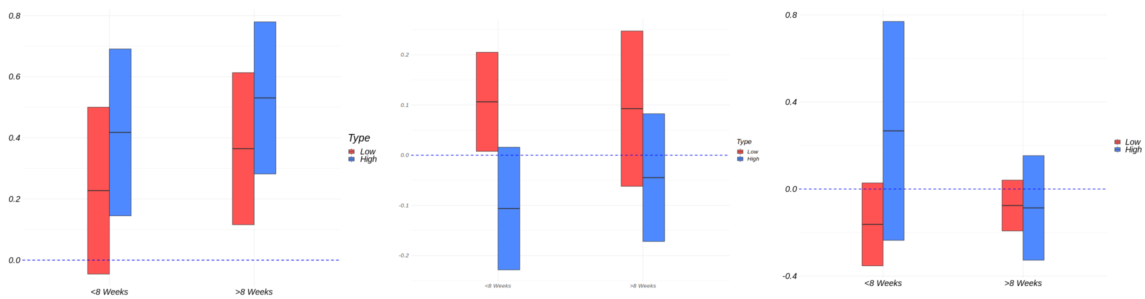
Figure E.13: Effect of Demand Shock on Absenteeism, by Manager Type (HT - 75th Percentile)



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.13 shows the percentage change in total absenteeism in a working group (car company), and in a store (fast food 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 27.41%; after eight weeks, it is 36%, while the effect of the High-training manager in the first eight weeks is -4.63%; after eight weeks, it is 2.65%. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 6.24%; after eight weeks, it is 27.04%, while the effect of the High-training manager in the first eight weeks is 20.8%; after eight weeks, it is -25%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is 24.97%; after eight weeks, it is 13.79%, while the effect of the High-training manager in the first eight weeks is -11.41%; after eight weeks, it is 4.72%. We compare the coefficients of both types of managers at an interval confidence of 83%.

Figure E.14: Effect of Demand Shock on Promotion, by Manager Type (HT - 75th Percentile)

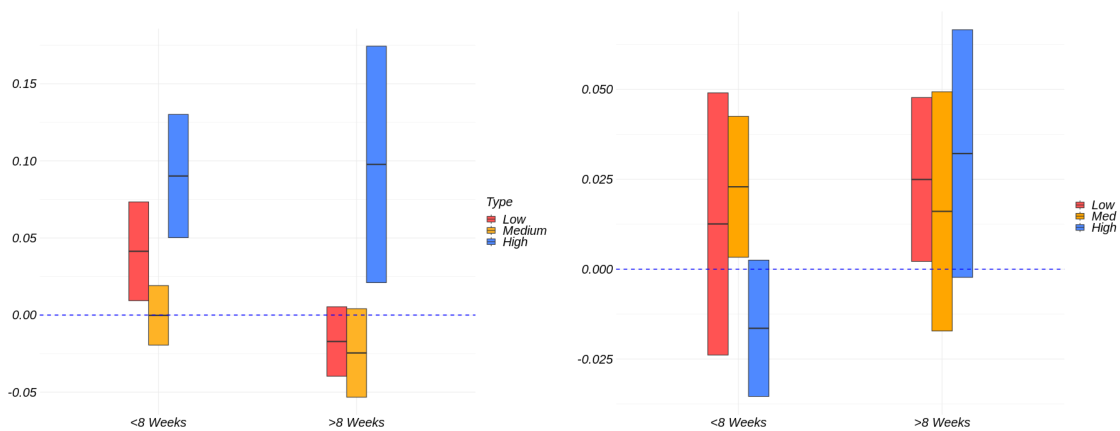


(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.14 shows the percentage change in total promotions in a working group (car company), and in a store (fast food 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 22.72%; after eight weeks, it is 36.44%, while the effect of the High-training manager in the first eight weeks is 41.78%; after eight weeks, it is 53.06%. For the fast food chain, the effect of the Low-training manager in the first eight weeks is 11%; after eight weeks, it is 9%, while the effect of the High-training manager in the first eight weeks is -11%; after eight weeks, it is -5%. Finally, for the retail company, the effect of the Low-training manager in the first eight weeks is -16.24%; after eight weeks, it is -7.58%, while the effect of the High-training manager in the first eight weeks is 26.72%; after eight weeks, it is -8.68%. We compare the coefficients of both types of managers at an interval confidence of 83%.

E.7.4 Terciles Analysis

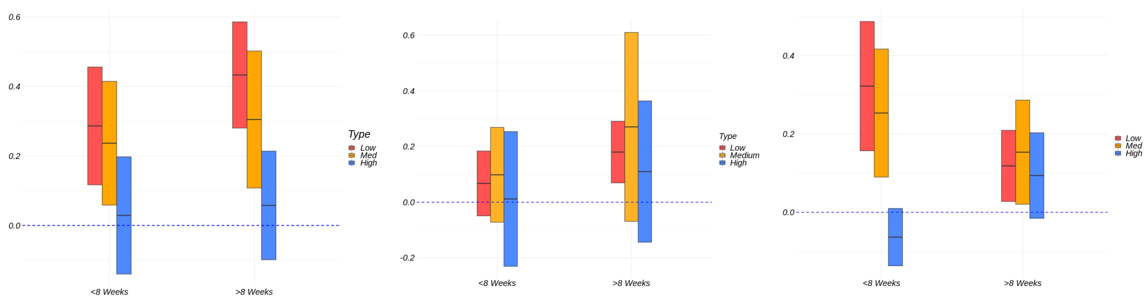
Figure E.15: Effect of Demand Shock on Performance (Sales), by Manager Type (terciles)



(a) Fast Food Chain (b) Retail Company

Figure E.15 shows the percentage change in total absenteeism in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. We analyze the 83% interval confidence for three types of managers: low-training managers which are managers with training FE below percentile 33, medium-type managers which are managers with training FE below percentile 66 and greater than percentile 33, and high-training managers, which are the managers with training FE greater than percentile 66. For the fast food chain, the effect of the 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 medium-training 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%.

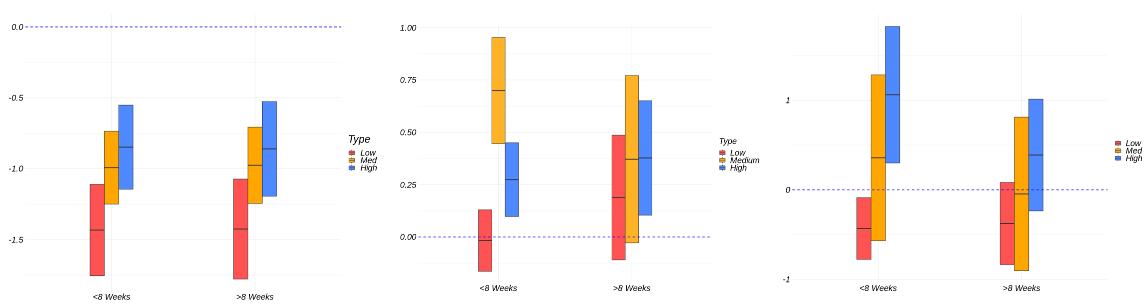
Figure E.16: Effect of Demand Shock on Absenteeism, by Manager Type (terciles)



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.16 shows the percentage change in total absenteeism in a working group (car company), and in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. We analyze the 83% interval confidence for three types of managers: low-training managers which are managers with training FE below percentile 33, medium-type managers which are managers with training FE below percentile 66 and greater than percentile 33, and high-training managers, which are the managers with training FE greater than percentile 66. 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 fast food 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%.

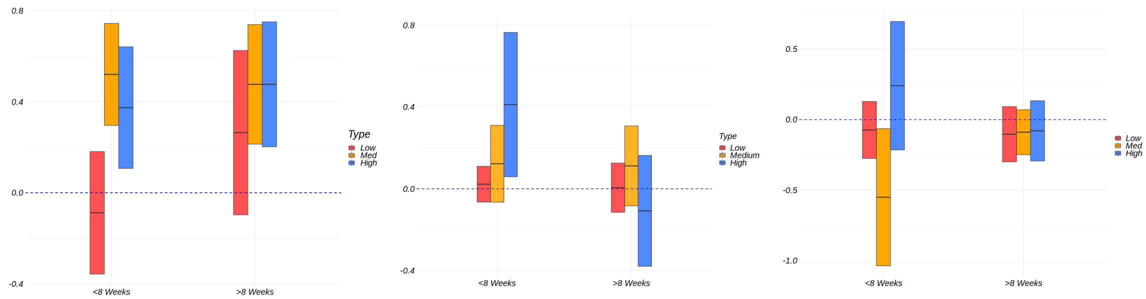
Figure E.17: Effect of Demand Shock on Training, by Manager Type (terciles)



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.17 shows the percentage change in total training in a working group (car company), and in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. We analyze the 83% interval confidence for three types of managers: low-training managers which are managers with training FE below percentile 33, medium-type managers which are managers with training FE below percentile 66 and greater than percentile 33, and high-training managers, which are the managers with training FE greater than percentile 66. For the car company, the low-training manager effect in the first eight weeks is -143.22%; after eight weeks, it is -142.49%, the medium-training manager effect in the first eight weeks is -99.21%; after eight weeks, it is -97.52%, while the effect of the high-training manager in the first eight weeks is -84.76%; after eight weeks, it is -86.01%. For the fast food chain, the effect of the low-training manager in the first eight weeks is -2%; after eight weeks, it is 23%, the medium-training manager effect in the first eight weeks is 70%; after eight weeks, it is 37%, while the effect of the high-training manager in the first eight weeks is 28%; after eight weeks, it is 39%. 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%.

Figure E.18: Effect of Demand Shock on Promotions, by Manager Type (terciles)

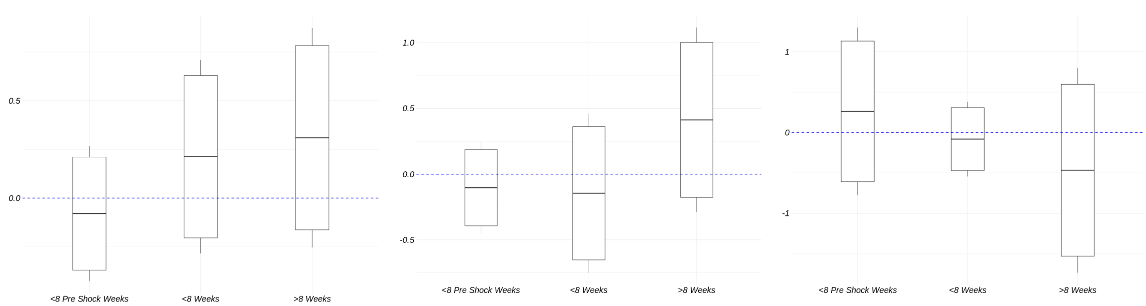


(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.18 shows the percentage change in total promotions in a working group (car company), and in a store (fast food and retail companies), eight weeks after the shock, and the effect after more than eight weeks. We analyze the 83% interval confidence for three types of managers: low-training managers which are managers with training FE below percentile 33, medium-type managers which are managers with training FE below percentile 66 and greater than percentile 33, and high-training managers, which are the managers with training FE greater than percentile 66. For the car company, the low-training manager effect in the first eight weeks is -8.80%; after eight weeks, it is 26.46%, the medium-training manager effect in the first eight weeks is -52.03%; after eight weeks, it is -47.93%, while the effect of the high-training manager in the first eight weeks is 37.42%; after eight weeks, it is 47.68%. For the fast food chain, the effect of the low-training manager in the first eight weeks is 5%; after eight weeks, it is 0%, the medium-training manager effect in the first eight weeks is 15%; after eight weeks, it is 13%, while the effect of the high-training manager in the first eight weeks is 42%; after eight weeks, it is -15%. Finally, for the retail company, the effect of the low-training manager in the first eight weeks is -7.32%; after eight weeks, it is -10.37%, the medium-training manager effect in the first eight weeks is -55.09%; after eight weeks, it is -8.54%, while the effect of the high-training manager in the first eight weeks is 24.09%; after eight weeks, it is -7.97%.

E.7.5 Splitting Employees by Cumulative Training before the Demand Shock

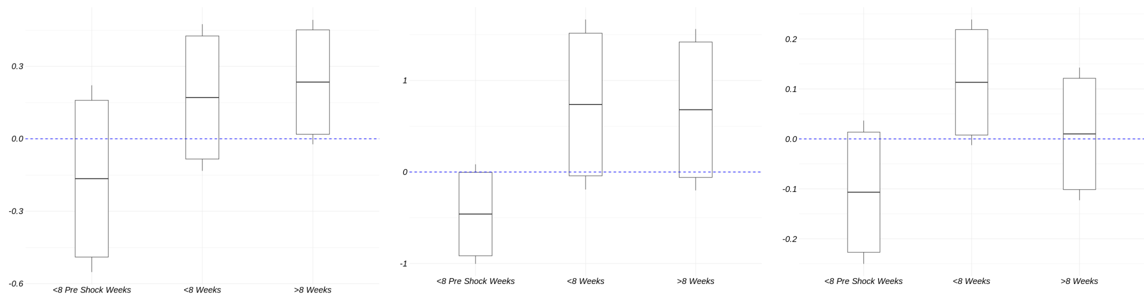
Figure E.19: Effect of Demand Shock on Absenteeism for High-Trained Employees



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.19 shows the HT effect on the percentage change in absenteeism for high trained employees before the shock, in a working group (car company), and in a store (fast food 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 21.29%; after eight weeks, it is 31.01%. For the fast food 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%. 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.

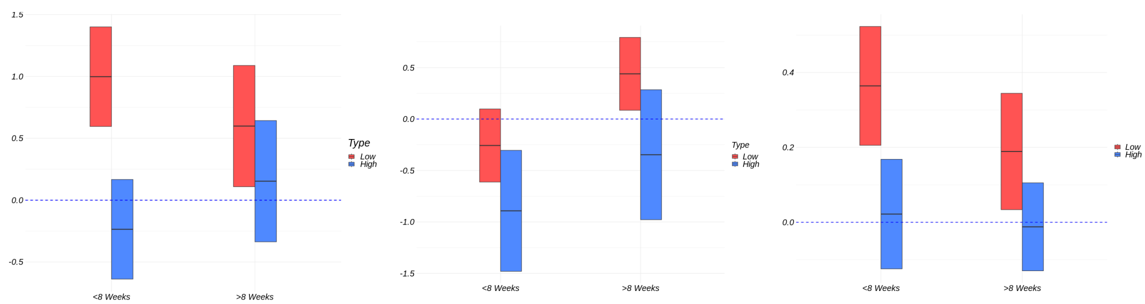
Figure E.20: Effect of Demand Shock on Absenteeism for Low-Trained Employees



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.20 shows the HT effect on the percentage change in absenteeism for low trained employees before the shock, in a working group (car company), and in a store (fast food 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 fast food 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%. 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.

Figure E.21: Effect on Absenteeism for Low-Trained Employees, by Manager type



(a) Car Manufacturer (b) Fast Food Chain (c) Retail Company

Figure E.21 shows the HT effect on the percentage change in absenteeism for low trained employees before the shock, in a working group (car company), and in a store (fast food 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 fast food 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%.

F Additional Tables

F.1 Car Company

Table F.1: Effect of Demand Shock on Production, Absenteeism, and Turnover

VARIABLES	(1) Total Cars produced	(2) Absent	(3) Turnover
Pre	82.53	-0.00672	0.0182
	(90.60)	(0.106)	(0.0113)
Post2	592.0*	0.251**	-0.00271
	(303.7)	(0.109)	(0.00707)
Post3	812.5**	0.360***	0.00379
	(297.6)	(0.0939)	(0.0137)
Constant	-240.5	-1.417***	-0.0628***
	(146.9)	(0.177)	(0.0200)
Observations	105	1,455	1,455
R-squared	0.654	0.437	0.100
Dependant Mean	1889.9616	1.11382	0.05442
Effects on the mean	0.3202	0.2064	-0.0217
Time FE	Monthly	Monthly	Monthly
Balanced	Balanced	Balanced	Balanced
Residualized Outcome	Yes	Yes	Yes
Managers	-	69	69
Managers treated	-	69	69

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

F.2 Fast Food chain

Table F.2: Effect of Demand Shock on Performance, Absenteeism, and Turnover

	(1) Sales	(2) Units	(3) Tickets	(4) Log Sales	(5) Absenteeism	(6) Turnover
Pre	0.648	500.1	196.1	0.0287	-0.252	0.0501
	(0.982)	(685.8)	(257.3)	(0.0230)	(0.200)	(0.0531)
Post2	3.052***	2,487***	784.2***	0.0884*	0.236	0.103**
	(1.052)	(858.9)	(275.2)	(0.0495)	(0.159)	(0.0498)
Post3	2.582**	2,761***	1,062***	0.0757**	0.469**	0.115*
	(1.129)	(854.2)	(347.7)	(0.0335)	(0.216)	(0.0634)
Constant	60.34***	37,502***	14,638***	3.949***	2.110***	0.0349
	(0.800)	(594.3)	(201.8)	(0.0244)	(0.133)	(0.0429)
Observations	2,146	2,146	2,146	2,146	2,146	2,146
R-squared	0.904	0.898	0.906	0.913	0.734	0.180
Dependant Mean	61.818	38,916.561	15,166.2493	3.9969	2.1813	0.1067
Effect on mean	0.0424	0.0623	0.0549	0.0182	0.1943	0.8464
Time FE	Biweekly	Biweekly	Biweekly	Biweekly	Biweekly	Biweekly
Balanced	No Balanced	No Balanced	No Balanced	No Balanced	No Balanced	No Balanced
Stores	83	83	83	83	83	83
Treated Stores	63	63	63	63	63	63

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

F.3 Retail Company

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

	(1)	(2)	(3)
VARIABLES	Log Transactions	Absenteeism	Turnover
Pre	0.0210	-0.526	0.260
	(0.0160)	(0.420)	(0.482)
Post2	0.0201*	0.685*	-0.168
	(0.0107)	(0.368)	(0.278)
Post3	0.0402***	0.407	0.474*
	(0.0134)	(0.348)	(0.266)
Observations	6,975	6,975	6,975
R-squared	0.983	0.792	0.229
Dependant Mean	11.35	6.54	1.71
Time FE	Biweekly	Biweekly	Biweekly
Balanced	No Balanced	No Balanced	No Balanced
Stores	83	83	83
Treated Stores	66	66	66

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

F.4 Car Company: HT effect on Absenteeism and Turnover

Table F.4: Car Company: Volume Shock and Good Management on Absent Employees and Turnover

	(1)	(2)
	absent	turnover
Post2	0.514***	0.00861
	(0.135)	(0.0120)
Post3	0.669***	0.0143
	(0.136)	(0.0227)
Postx2Treat	-0.542***	-0.0226
	(0.169)	(0.0165)
Postx3Treat	-0.637***	-0.0210
	(0.184)	(0.0293)
Constant	-1.361***	-0.0705**
	(0.241)	(0.0321)
Observations	1,455	1,455
R-squared	0.393	0.083
Linear Combination P2	-0.027	-.014
Linear Combination P3	0.032	-.007
Dependant Mean	1.11382	.05442
Time FE	Monthly	Monthly
Balanced	Balanced	Balanced
Residualized Outcome	Yes	Yes
Managers	69	69
Managers treated	69	69

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

F.5 Fast Food Chain: HT effect on Absenteeism, Turnover and Sales

Table F.5: Fast Food Chain: App Shock and Good Management on Absent Employees, Turnover and Sales

	(1) Absenteeism	(2) Turnover	(3) Sales
Post2	0.104	0.102**	2.790
	(0.234)	(0.0508)	(1.750)
Post3	0.653**	0.141*	-1.470
	(0.251)	(0.0816)	(1.164)
Post2xTreat	0.102	-0.00530	0.950
	(0.378)	(0.0842)	(2.071)
Post3xTreat	-0.581*	0.0349	4.692*
	(0.302)	(0.123)	(2.416)
Constant	2.233***	0.0573**	62.07***
	(0.0801)	(0.0216)	(0.330)
Observations	1,809	1,809	1,809
R-squared	0.735	0.161	0.898
Linear Combination P2	.206	.097	3.74 **
Linear Combination P3	.072	.176 *	3.222
Dependant Mean	2.3975	.1144	62.3259
Time FE	Biweekly	Biweekly	Biweekly
Balanced	No Balanced	No Balanced	No Balanced

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

F.6 Retailer Company: HT effect on Sales, Absenteeism and Turnover

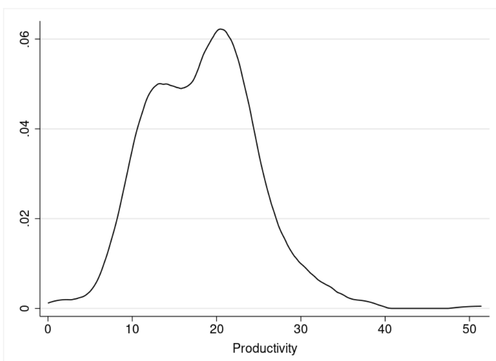
Table F.6: Retail Company: Delivery App Shock and Good Management on Sales, Absent Employees and Turnover

	(1) Log Transactions	(2) Absenteeism	(3) Turnover
post_2	0.0127	2.133***	0.165
	(0.0215)	(0.679)	(0.260)
post_3	0.00940	0.713*	0.371*
	(0.0152)	(0.413)	(0.222)
Post2xTreat	-0.0169	-2.177***	-1.128
	(0.0223)	(0.691)	(0.890)
Post3xTreat	0.0319	0.0945	-0.198
	(0.0232)	(0.580)	(0.316)
Observations	6,975	6,975	6,975
R-squared	0.983	0.793	0.229
Linear Combination P2	-.00426523	-.0433894	-.96280824
Linear Combination P3	.04133632 **	.80790056 *	.17351583 *
Dependant Mean	11.35	6.54	1.71
Time FE	Biweekly	Biweekly	Biweekly
Balanced	No Balanced	No Balanced	No Balanced
Stores	83	83	83
Treated Stores	66	66	66

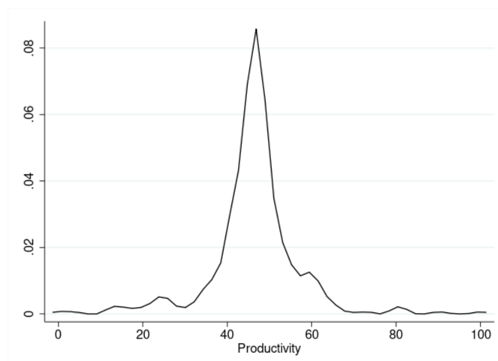
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

F.7 Manager Productivity Fixed Effects Distribution

Figure F.1: Manager Productivity Fixed Effects Distribution



(a) Fast Food Chain



(b) Retailer

Figure F.1 shows the manager fixed effects distribution for the Fast Food and Retail companies, when we use as an outcome the productivity. 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.