PRODUCTIVITY TRAINING AND WORKER INDEPENDENCE: EVIDENCE FROM INDIA

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December 5, 2025

Abstract

Training programs are an important way for firms to enhance productivity, particularly in developing economies where workforce skill levels are often low. This paper evaluates a training program aimed at improving production practices among operative workers. Using a difference-in-differences approach on shift-level data from 2000 to 2002, I estimate the effects of the training on productivity and output per worker, with a focus on shifts where middle managers are absent. I find that the training program mitigates the disruption caused by management absenteeism, increasing productivity and output by 10% to 20% in shifts affected by middle manager absences. This paper contributes to the literature studying training in firms by demonstrating the critical role of middle managers in low-skilled environments and the potential of targeted training programs to reduce disruptions arising from their absences.

Keywords: worker training, productivity, management absenteeism, developing countries, manufacturing, production function, difference-in-differences.

JEL classification: J24, M53, M54, O14, O12

Acknowledgments. I am deeply grateful to my advisors, Andrea Weber and Tímea Molnár, for their continuous guidance, encouragement, and invaluable feedback. I also thank Ádám Szeidl, Marc Kaufmann and Sergei Lychagin for their helpful comments and suggestions. I am indebted to Sergei Lychagin for his helpful support to obtain the data. I thank participants at the Vienna PhD Workshop, internal seminars, and Young Economist Conference for valuable comments. All remaining errors are my own.

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1 Introduction

Training of workers is a critical investment for firms to increase their productivity. According to the Association for Talent Development (ATD)[1], U.S. companies spent approximately 101.8 billion USD on training and development in 2020, with an average expenditure of 1111 USD per employee, primarily focusing on improving soft and technical skills. According to a survey of workers in more than 3000 multinational firms worldwide by the LinkedIn Learning Report in 2019[2], 94% of employees would be more likely to stay at a company longer if it invested in their career development and training. Moreover, the World Economic Forum (WEF) in a 2023 report[3] emphasized that 50% of all employees will need re-skilling by 2030, due to the increasing adoption of new technologies and automation.

In this paper, I study how a training program to improve production practices of operative workers increased output and productivity by mitigating the effect of middle managers' absences. The training program focused on improving production practices of operative workers and it took place in a large rail mill in India with the goal of raising firm total output and productivity. To the best of my knowledge, I am the first to estimate how a training program can mitigate the disruption on output and productivity caused by the absenteeism of the management. Before the training was implemented in June 2001, workers relied heavily on their middle managers to solve small problems on the production line, resulting in a highly vertical and inefficient organizational structure. Although the formal structure of the production facility remained unchanged, the training was successful in its goals and it was able to reduce the impact of absences of middle managers.

I find that this training was successful in increasing output, productivity and in mitigating the negative effect of manager absences on production. I estimate that absences of a middle manager decrease output produced per worker during a shift between 15% and 20% while productivity, measured as output per minute worked, decreases by around $0.09 - 0.17$ units across different specifications. I find that the training program increases productivity raising output per minute in shifts without any manager absence by around 0.02 and 0.45 units, similar to the results in Somanathan et al. (2010). I also estimate that the training decreases the amount of unexpected stoppages of production caused by worker mistakes and increases output per worker by 8% and 15%. In addition, the effect of training is much larger in shifts where middle managers are absent. In shifts where a middle manager is absent,

[1]2020 State of the Industry Report, AED
[2]2019 LinkedIn Learning report, LinkedIn.com
[3]Future of Jobs Report 2023, WEF

total output per worker raises by $15\% - 20\%$ while productivity by around $0.09 - 0.15$ output produced per minute after the training is completed, compared to similar shifts affected by such absences in the pre-training period. In summary, I find that manager absences reduce productivity and lower overall output. However, the training program proved effective in decreasing worker-caused production stoppages, which in turn increased output per worker. The training also had a particularly strong effect during shifts affected by manager absences: when a manager was absent during a shift, productivity improved significantly after the training, leading to an increase in total output per worker produced during those shifts. On the other hand, I find no significant effects of training for other types of output different from rails that were not targeted by the program.

The training took place in Bhilai Rail and Structural Mill, a factory owned by the Steel Authority of India Ltd. (SAIL). SAIL has been the major player in India for the production of rails and components for infrastructure projects since the 1960s but its role was at risk by the end of the century. Low output levels in the 90s and concerns about output quality pushed the company to improve their products through training of operative workers and improvements in physical capital. In 1997 Indian railways expected an increase in output from SAIL factories to expand their infrastructures, pushing SAIL mills to increase output to meet the raising demand for expanding the railway system in India. Later on, a large railway accident in 1998, attributed to low-quality rails, raised doubts about SAIL's ability to meet quality and quantity standards. Therefore, pressure on SAIL to improve the quality of output and increase production rose significantly in this situation. To achieve these goals SAIL decided to organize training programs across its production sites to improve output quality and improve the ability to fulfill larger orders in the short term while upgrades to physical capital were programmed only for years after 2003. As a result of these programs, production and quality of rails increased, and SAIL was able to maintain its role as the monopolistic supplier for the Indian railways as found in Somanathan et al. (2010).

I use personnel data of Bhilai Rail and Structural Mill between June 2000 to June 2002 exploiting the same dataset used in Somanathan et al. (2010). This dataset collects over 1900 different 8 hours work shifts. It contains detailed information on operative workers and managers presence at work, output, delays, time worked, defective output and the type of product made in each shift, distinguishing between rails or other components produced for large infrastructure projects. It also includes data on workers' characteristics and their job designations. From these data, I constructed a shift-level dataset that contains the average characteristics of workers present on the production line, type of output made, production outcomes, number of workers working at each machine, team working on the production line and the number of managers present.

I use a Difference-in-Differences model to estimate the effect of training on production outcomes. I use production per worker, output per minute worked in a shift, percentage of defective output and unexpected production delays as outcome variables. I focus on shifts where managers are absent, as I expect the training program to have the most significant benefits in these cases. I use shifts affected by manager absences as the treatment group while I use June 2001 as the cutoff date for pre and post training periods. In this way, I can estimate the effects of the training in shifts where at least one manager was absent. I use inverse propensity score weighting and nearest neighbor matching in my regressions to compare shifts with similar observable characteristics using month, number of workers present in each role, team on duty, average team tenure and average team age as matching variables. Then, I estimate the model without any matching or weighting, I exclude shifts affected by planned maintenance stoppages and I implement an event study design to examine anticipatory and persistent effects of middle manager absences on output around the days of absence. With these regressions, I also estimate the effects of middle manager absences on production outcomes.

The training effect is in line with estimated effects in the literature of short training programs in developing counties and with low skilled workers. The estimated impact of this training program is comparable to other papers with training increasing output and productivity up to 20% (De Grip and Sauermann, 2012; Konings and Vanormelingen, 2015; Dearden et al., 2006; Liu and Batt, 2007), although comparisons across different industries and training types can be difficult. Moreover, I will show results not only on total output and productivity measured as output per minutes worked but also on other production outcomes such as shifts affected by unexpected delays and percentage of defective output.

There is extensive literature on the impact of absenteeism on firms (Muchinsky, 1977; Kocakulah et al., 2016; Kampkötter and Marggraf, 2015; Grinza and Rycx, 2020) and the effectiveness of training programs (Ashenfelter, 1978; Bartlett, 2001; Ballot et al., 2006; De Grip and Sauermann, 2012; Ji et al., 2012; Elnaga and Imran, 2013; Niati et al., 2021). However, to the best of my knowledge, I am the first to estimate how a training program for operative workers was able to mitigate the effects of middle managers' absences on output and productivity and how such absences affect these outcomes in a context of a firm in a developing country where the workforce is characterized by low training and education. Therefore, I make two main contributions to the literature on training programs and absenteeism: I examine the impact of middle manager absences on output and productivity and I analyze how a training program can help mitigate this effect.

First, I show empirical evidence on how middle managers are important for firms in a developing economy with low skilled workforce by studying the impact of their absences on production. Absenteeism is a relevant problem in developing countries, for instance, Duflo et al. (2012) use an Randomized Control Trial (RCT) to study how to reduce absenteeism among teachers in India. Tumlinson et al. (2019) report that half of healthcare facilities surveyed in their work show high levels of absenteeism in their workforce such as not showing up at the workplace, arriving late or leaving early. Belita et al. (2013) find that absenteeism is likely to further affect healthcare deprivation in low-income counties. In this paper. I focus on managers given their key role in firms' organization (Lucas Jr, 1978; Bloom et al., 2013b). Compared to these papers and other of the related literature on absenteeism (Noorbakhsh et al., 1999; Khadria, 2006; Hajela, 2012; Sharma, 2024), I focus on the effects of middle manager absences on production instead of absenteeism among operative workers.

Second, I study how a training program to improve production practices among operative workers is effective in raising productivity and output by reducing impact of middle managers' absences. Related studies, estimated the effect of training using balance sheet data or large industry-level surveys (Ballot et al., 2006; Conti, 2005) but missing the specificity of each different type of training program across different firms and industries. Additionally, there is a relevant stream of literature that used RCTs to estimate the effect of management training on firms' productivity and output but without focusing on operative workers (Bloom et al., 2013a; McKenzie, 2021), or without investigating the specific mechanism for the success of the programs (De Grip and Sauermann, 2012; Konings and Vanormelingen, 2015) as I do in this paper.

The paper closest to this is Somanathan et al. (2010) that uses this same dataset to analyze the overall effect of this training program. They estimate shift-level regressions and find that one additional day of training increases rail output per worker by 0.25 units. However, they study the general effect of the training program on production without focusing on how it mitigates the effect of manager absences. In contrast to this paper and the previous literature on training, I study through which channel this training program, aimed at improving production practices among operative workers, was effective in improving productivity and output.

For the rest of this paper I proceed as follows: in section 2, I describe the setting. In section 3, I explain the dataset. In section 4, I present a theoretical model of production with managers and workers. In section 5, I present the econometric framework. In section 6 and 7, I present descriptive statistics and the empirical results. In section 8 I discuss the results while, in section 9, I conclude.

2 Setting

2.1 The Factory

Bhilai Rail and Structural Mill, is a production facility owned by the Steel Authority of India Limited (SAIL) and it is a public sector plant specialized in the production of *rails* for the Indian railway network and *structurals* that are components for industrial machines and beams for infrastructure projects. SAIL, a major player in India's steel industry, operates large production sites for steel products and is the sole supplier of rails for Indian railways. The Bhilai plant was established in the 1960s with Soviet cooperation, along with other plants across rural India. These facilities aimed to develop the country's industrial sector at a time where agriculture was still predominant. Located in Bhilai, close to nearly 100 villages, the factory played a crucial role in the region's development by prioritizing well-paying jobs for local residents and fostering economic growth in what was then a deprived area.

Workers in Bhilai Rail and Structural Mill are organized in a highly standardized way, following the assembly line shift system. Work is managed into eight-hour shifts, with each team, consisting of the same workers, assigned to one of the three daily shifts for a week. The following week, each team rotates to a different shift, ensuring that over three weeks, every team completes one week of morning shifts, one week of afternoon shifts, and one week of night shifts. Workers responsible for production are divided into two main categories: middle managers and operative workers. Middle managers help operatives and they are to supervisors of the whole production line. Operative workers handle different machines and specific tasks, while middle managers coordinate the assembly line and assist operative workers in their duties. The firm employs around 250 operative workers contemporaneously and they are permanently assigned to their teams since changes in team assignments are rare. Operative workers usually have a low level of education as many report to have studied until 5^{th} or 8^{th} grade. In each shift there are around 75 operative workers and 2 middle managers.

Bhilai rail and structural mill has one production line within the mill and it is divided into three sections, with operative workers responsible for specific tasks at each stage. First, steel blooms are heated in the furnace at the start of the production line. Next, the hot steel moves to the mill area, where it is shaped according to the desired output. Finally, the steel is cut in the hot saw area and placed in the cooling bed to cool down, completing the production process. In the furnace section, there are three types of workers: service workers, who record the blooms heated up; control operators, who manage the steel in the furnace machines; and operatives, who ensure the correct functioning of the equipment. In the mill section, control operatives and coggers are responsible for rolling the rails, while operatives and plant attendants ensure the smooth operation of the machines. In the final stage, the saw spell team cuts the heated and rolled steel to produce and craft the final output. Throughout the entire production line, technicians address machine issues, and crane operators transport the steel blooms between sections.

The structure of the production facility remained constant throughout the period of analysis, with no organizational changes occurring during this time. Workers join the firm and receive a brief, informal training on operating the machines they are assigned to and this assignment is usually permanent. Team composition also remains stable over time, as it is uncommon for workers to be reassigned to different teams. The firm typically employs eight middle managers and two of them are in charge in each shift. They are allocated to shifts without a strict association to specific teams and this arrangement did not change during the period I am studying.

Absences are recorded for both operative workers and middle managers. The company documents the reasons for operative worker absences, categorizing them into sickness, unexpected absences, planned absences, or rest days. However, for middle managers, absences are recorded without specifying the reasons. As a result, I cannot differentiate between the specific causes of manager absences. In the following sections, I explain how I address this limitation in my identification strategy.

2.2 The Training Program

SAIL had a longstanding procurement contract with the Indian government for the production of steel rails since the 60s. But in 1997, new targets of production were assigned from the government to SAIL and to the Bhilai Rail and Structural Mill in the government five year plan as Indian railways asked for an increased supply of rails[4]. The targets were below the theoretical capacity of the facility but largely above the production level. Therefore, for the first time, the government started to ask alternative suppliers about the possibility of setting up new production sites to cover the increased demand for rails. The pressure to enhance both quantity and quality intensified after a major train accident in 1998, attributed to the misconstruction of rails purchased from SAIL where more than 200 people were died.

From 1999 to 2003, SAIL's future was marked by high uncertainty due to the near finalization of deals by Indian Railways with alternative suppliers as written in press reports[5]. During this period, an alternative supplier, Jindal Steel and Power Limited (JSPL), almost secured a deal with Indian Railways for the construction of a new rail mill starting in late 2001 as reported in parliamentary debates reading rail procurements. This agreement would have put jobs in SAIL and, consequently, in Bhilai Rail and Structural Mill at risk. These projects were halted by an agreement between SAIL, the Ministry of Railways and the Ministry of Steel in October 2001 where the government committed to keep the procurements exclusively with SAIL, contingent upon new investments in physical and human capital to increase output and improve quality. Finally, in February 2003, the decision to retain SAIL as the sole supplier was officially confirmed as pointed out in company and ministry documents.

During this period, the workers and the management at the Bhilai mill and in other SAIL facilities faced significant pressure to meet the new production targets to safeguard the company's market share and their jobs. In the short term, before new investments financed by the Ministry of Railways were realized, alternatives had to be found to improve performances without any increase in physical capital or in the workforce, in order to convince the government not to withdraw from the longstanding procurement contract it had with SAIL. Consequently, new training programs were organized across SAIL in its production facilities to boost human capital and improve both quality and productivity of the production facility. After 2003, training programs were supported by upgrades and increases in physical capital.

In this context, a major training initiative was launched in June 2001 in Bhilai Rail and Structural Mill to boost rail production outcomes in the mill. The program lasted over two weeks and the production line was halted during this period. Although workers from var-

[4] https://cprindia.org/wp-content/uploads/2022/12/Ninth-Five-Year-Plan-1997-2002.pdf

[5] (Jyoti Mukul, "Railways to procure Rs 400 cr worth rails from Bhilai Steel," Indian Express, June 9, 2000.

ious divisions of the Bhilai factory participated, the program primarily involved operative workers. Over 80% of production line workers participated in at least one session of training, with many of them attending for two or more. In the official company records, senior management described the training program with the following objectives: "Increasing Rail Dispatch to 1800 t/day" and "Increasing Rail Acceptance in RSM (PEP)". Searching in online reports from the steel industry, similar terms as those found in the description of the training are linked to programs that aim to improve production practices of operative workers to increase their productivity [6][7]. According to Somanathan et al. (2010), the training project was set up to improve knowledge of workers about the new changes in the market for steel and focus groups were created to discuss ways to improve productivity to meet the new production targets. Moreover, a former employee of the firm, said that a key part of this training was devoted to spread knowledge of correct production practices across the workforce.

Workers in the firm were heavily reliant on middle managers, and the primary goal of the training was to enhance the ability of workers to carry out their tasks independently, thereby reducing their dependence on managerial support. Middle managers are responsible for coordinating the production line as their main duty and for assisting workers if any problem arises. Prior to the training, workers frequently required middle managers' support to complete many of their daily tasks. The production line, which stretched over one kilometer, posed significant logistical challenges for middle managers to move around and help everyone who needed. With only two middle managers per shift, they were often occupied assisting workers at different points along the line instead of focusing on coordinating the production line, their main task. To address this issue, the top management at the production facility aimed to enhance the production practices of operative workers and their ability to perform tasks independently. The goal was to reduce the time middle managers spend assisting operative workers, prevent production delays and increase overall productivity.

3 Data

In this paper, I use a dataset with highly detailed personnel information from Bhilai Rail and Structural Mill from Somanathan et al. (2010), covering the period from June 2000

[6] https://www.railwayage.com/mw/trashed-7/.
[7] https://it.scribd.com/document/149524345/28-Operator-Training

to June 2002. It includes one year of data before the training and one year after, and is divided into five smaller sub-datasets: attendance records, qualifications, personnel data, production data, and training reports.

The first dataset contains detailed information on daily attendance, including the shift assignments for each worker, their roles on the assembly line and the specific reasons for absences. I use this dataset to determine the total number of workers on the production floor and their distribution across various roles in the production line: service workers, crane operators, control operators, furnace operatives, SCM team, mill operatives, plant attendants, saw spell team, and technicians. I have information on the specific reason of absences for operative workers but not middle managers.

The second and third datasets collect the qualification and personnel data, which contain personal information about the workers. The most important variables I use include the date of joining the firm, birth date, caste, birth location, education level, and the year of obtaining a school degree. I combine these datasets with the attendance records to present summary statistics on work shifts. Additionally, I use this information in the empirical analysis as control variables in the regression or as explanatory variables to estimate the propensity scores in matching.

The fourth dataset records all the production data for every shift from June 2000 to June 2002. This dataset is key for the econometric analysis. It includes the amount of steel blooms transformed in output during each shift, amount of defective output, the shift timings, the team in charge of the production line, production delays and their causes, the middle managers overseeing the shifts along with any absences, and the type of output produced (rails or structural components). I use this information to estimate the effect of training on output when production managers are absent.

The fifth and final dataset have information on training provided to workers. It records each training session undertaken by workers, including the start and end dates and a brief description of the program content. Various training programs were assigned to operative workers, with the most frequent focusing on achieving ISO standardized qualifications for environmental and safety practices. Additional training covered cost reduction practices, soft skills (motivational training), safety, and productivity enhancement. In this paper, I focus on a large productivity training program organized in June 2001, aimed at improving work practices on the production line.

4 Model of Production

I present a simple Cobb-Douglas production function of a firm that uses complementary inputs to describe its production process in the assembly line. In this model, I distinguish between two types of inputs: operative workers who operate the machines and the managers who supervise the production process. Additionally, the model includes a parameter that represents the dependence of operative workers on managers to complete their tasks.

The production function is as follows:

$$Y = AM^{\alpha(\delta)}O^{\beta(\delta)}$$

Y is the output, A is a constant production scaling parameter, M is managers, O is operatives, α and β are the output elasticities for the different inputs and δ is a parameter representing the dependency of operative workers on managers. α, β are parameters ranging between zero and one.

I assume $\alpha(\delta)$ and $\beta(\delta)$ to be positive, $\alpha(\delta) = \delta$ and $\beta(\delta) = 1 - \delta$, $\delta \in (1/2, 1)$ to consider the fact that managers are always more productive than operative workers and $\alpha + \beta = 1$ (constant returns to scale). Marginal productivity of operative workers and managers depends on δ. As δ decreases, operative workers become less dependent on their managers, $\alpha(\delta)$ decreases and $\beta(\delta)$ increases.

$$\alpha'(\delta) > 0 \qquad \beta'(\alpha) < 0$$

Then, I compute how output changes with respect to δ and M by studying the partial derivatives of the production function:

1. First-order derivative with respect to M:

$$\frac{\partial Y}{\partial M} = AO^{1-\delta}M^{\delta-1}\delta$$

2. The second-order derivative of the production function, first with respect to M and then with respect to δ, is:

$$\frac{\partial^2 Y}{\partial M\,\partial \delta} = A\Big[\delta O^{1-\delta}M^{\delta-2}(\delta-1) + M^{\delta-1}O^{1-\delta} - \delta M^{\delta-1}(1-\delta)O^{-\delta}\Big]$$

The first and third terms of the sum in this equation are negative, while the second term is positive. Under the assumptions of the model, when δ close to one, indicating that operative workers are highly reliant on managers, then $\frac{\partial^2 Y}{\partial M \partial \delta} > 0$ because when $\delta \to 1$ the first and third term of the above sum tend to zero while the second term would go to one. This implies that a decrease in δ leads to a reduction of the marginal productivity of managers and to an increase of the marginal productivity of operative workers.

Analyzing the above equations, reducing dependence of operative workers on supervisors decreases the importance of managers in production. Focusing on point 2, decreasing δ reduces the marginal impact of managers on output Y. Consequently, in scenarios where operative workers decrease reliance on their supervisors, absences of managers have a smaller effect on output produced. These conclusions are valid also for the case of decreasing returns to scale ($\alpha(\delta) + \beta(\delta) < 1$).

5 Econometric Framework

To study the effects of training on production outcomes, I use a difference-in-differences model to estimate the effect of training in shifts where managers are absent. The training to improve practices for production of rails took place in June 2001. I compare shifts before and after the training using shifts with absences as treatment group and shifts without manager absences as control group in this setting. I use this specification since the only change in the period between 2000 and 2002 was the training program while capital upgrades were expected only later on, according to sources from the firm, thus avoiding confounding threats. Therefore, I am comparing shifts with and without middle manager absences with similar production inputs before and after the training. The equation is as follows:

$$y_{izt} = \beta_0 + \beta_1 Abs_{izt} + \beta_2 Post_t + \beta_3 Post_t * Abs_{izt} + \gamma_z + \tau_t + \eta_i + \theta X_{izt} + \epsilon_{izt} \qquad (1)$$

In this regression equation, I use four outcome variables y_{izt}: rolling rate, log output per worker, unexpected delays and the ratio of defective output in shift i by team z in month t. Rolling rate is defined as the ratio of output to the minutes of working time during a shift, with the shift work time being eight hours minus any downtime due to delays. Log output per worker is calculated as the log of the ratio of final output to the number of workers present on the production line. Unexpected delays is a categorical variable that define if production during a shift has been unexpectedly stopped at least once. The ratio of defective output is the proportion of defective final output to the total output produced in a shift.

I estimate the difference in differences model by using absences, training and fixed effects. The independent variables are mangers absences, denoted as Abs_{izt}, which is an indicator for a shift to have at least a manger absent, and $Post_t$, a binary variable indicating whether the observation occurs after a training program, with a value of 1 for post-training and 0 otherwise. The interaction term, $Post_t * Abs_{izt}$, explores whether the effect of absences on the outcomes differs before and after the training. Additionally, fixed effects for the month, shift and team denoted as τ_t, η_i and γ_z, respectively, account for time, team, shift-specific unobserved heterogeneity that could influence the dependent variables. X_{izt} represents a vector of shift-level control variables that might affect the outcomes such as number of workers present on the assembly line by job designation. I cluster standard errors at the team by month level.

I use shifts with absences and the post-treatment period to identify the effect of training. Since I do not have any shift unaffected by training in the post-training period, I estimate the effect of training on production and on absence mitigation, β_2 and β_3, by comparing shifts affected or not by manager absences. To address possible observable differences among shifts with or without manager absences, I employ matching methods to mitigate this concern. For example, a possible threats to identification could be the fact that some shifts are dedicated to slightly different type of production within rails or structural output and using matching alleviates this problem.

I estimate propensity scores using a logistic regression separately for the pre and post training periods. I run two different regressions to estimate the propensity scores: one for shifts before the June 2001 training and one for shifts after. I compute inverse propensity score weights to estimate the regressions on the matched samples or by including weights in the estimation. The propensity scores and propensity score weights are estimated as follows:

$$p(Abs_{izt}) = f(\alpha_i + \gamma_z + \tau_t + \theta X_{izt}) + \epsilon_{izt}$$

$$\text{For treated observations } (Abs = 1): \quad \hat{w}_{izt} = \frac{1}{p(Abs_{izt})}$$

$$\text{For untreated observations } (Abs = 0): \quad \hat{w}_{izt} = \frac{1}{1 - p(Abs_{izt})}$$

I use the estimated probability of having a manager absence $p(Abs_{izt})$ to compute weights $\hat{w}_{izt}$ to be included in the matched regressions. I estimate the propensity scores using a vector of observable characteristics X_{izt}. This vector includes number of workers present in each section in every shift, average team tenure and average team age, γ_z is team fixed effect while, τ_t is month fixed effect and α_i is shift fixed effects. I estimate propensity scores separately for shifts producing structural components or rails. I use inverse propensity score weights in my main specification to re-weight the data so that shifts with and without absences are comparable in terms of observed characteristics and to give more weight to shifts affected by middle manager absences with observable characteristics more similar to shifts in the control group, and vice-versa (Hirano and Imbens, 2001). Then, I exploit propensity scores to create a nearest neighbor matching and nearest neighbor matching with exact matching samples for additional analysis. Exact matching ensures that the nearest neighbor is selected such that treated and untreated observation pairs are constrained to have at least a variable sharing the exact same value.

I use a difference in differences specification with inverse propensity score weighting as my main specification. First, I include inverse propensity scores as weights in this regression to alleviate the concern of differences between treated and control shifts in observable characteristics. As robustness checks, I estimate the regression equation without any matching or weighting using shifts with absences as treatment group and shifts without absences as control group. Then, I estimate the regression on the nearest neighbor matched sample. Third, I estimate the regression using exact matching, so that shifts in the treatment and control group pairs are operated by the same team. Fourth, I estimate the main regression excluding shifts during which more then half of the time was not worked due to planned maintenance. Shifts heavily affected by these operations might require a different number of managers and workers on duty around the assembly line affecting the correct estimation of the regression coefficients if these maintenance operations are not random and changed their frequency before and after the training program. Then, I use a simple event study design model to estimate eventual anticipatory and persistent effects of middle manager absences on output.

6 Summary Statistics

I present summary statistics for shifts at the Bhilai Rail and Structural Company from June 2000 to June 2002. These statistics are useful for illustrating the reduced-form results between pre- and post-training months, as well as the descriptive characteristics of shifts with and without absences. I show descriptive statistics for the matched samples to demonstrate that matching can balance differences in observable characteristics between these shifts. Since some absences are expected and shifts may be organized differently, I use matching to retain only those shifts with absences similar to those without absences. This approach tries to mitigate the issue of expected absences.

In table 1, I the present summary statistics comparing observable characteristics of shifts with and without manager absences. On the left side, I show a comparison of observed characteristics of shifts, such as the number of workers present on each machine, tenure, cast composition and the age of the workers, between the two groups.

Table 1: Balance Table: Unmatched and Matched Samples

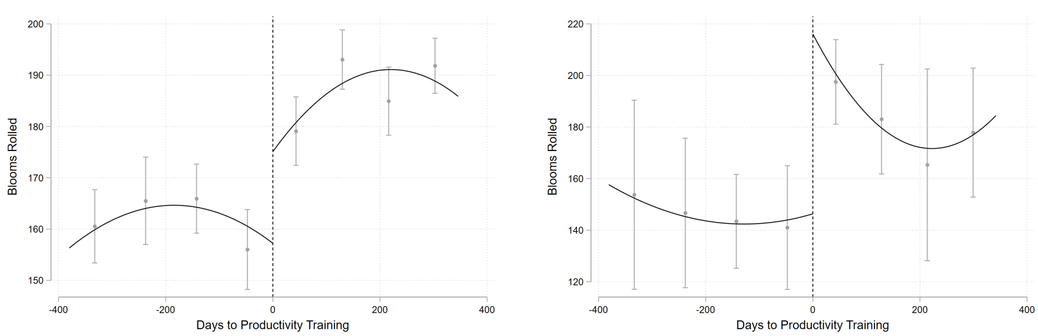
	Unmatched						**Matched**					
	No Absences		Absences		Difference		No Absences		Absences		Difference	
	Mean	SD	Mean	SD	Diff	p-val	Mean	SD	Mean	SD	Diff	p-val
Floor Workers	63.96	(4.71)	62.16	(5.35)	1.80***	(0.00)	61.79	(4.75)	62.16	(5.35)	-0.37	(0.49)
Cast Share	0.65	(0.04)	0.64	(0.05)	0.01***	(0.00)	0.64	(0.04)	0.64	(0.05)	0.00	(0.97)
Team Age	39.94	(0.65)	39.75	(0.72)	0.20***	(0.00)	39.77	(0.66)	39.74	(0.72)	0.03	(0.68)
Team Tenure	14.90	(0.70)	14.82	(0.79)	0.09	(0.11)	14.85	(0.71)	14.81	(0.78)	0.04	(0.61)
Workers Control Furnace	5.35	(1.47)	5.39	(1.45)	-0.04	(0.72)	5.25	(1.40)	5.41	(1.43)	-0.16	(0.29)
Workers Crane	4.80	(1.05)	4.52	(1.06)	0.28***	(0.00)	4.51	(1.06)	4.53	(1.06)	-0.02	(0.88)
Workers Operative Furnace	2.20	(0.94)	1.99	(0.93)	0.21**	(0.00)	1.95	(0.82)	2.00	(0.93)	-0.05	(0.56)
Workers Operative Mill	17.84	(2.19)	16.64	(2.26)	1.21***	(0.00)	16.52	(2.19)	16.61	(2.24)	-0.09	(0.69)
Workers Plant Attendant	3.09	(1.21)	3.26	(1.00)	-0.17	(0.06)	3.23	(1.12)	3.26	(1.00)	-0.04	(0.73)
Workers Re-Heating	3.97	(0.80)	3.87	(0.87)	0.10	(0.11)	3.88	(0.87)	3.87	(0.87)	0.02	(0.86)
Workers Saw Spell	4.61	(1.42)	4.67	(1.35)	-0.06	(0.55)	4.60	(1.42)	4.68	(1.35)	-0.08	(0.57)
Workers SCM Team	15.07	(2.05)	14.63	(2.19)	0.44**	(0.01)	14.83	(2.05)	14.60	(2.16)	0.23	(0.30)
Workers Services	5.76	(1.19)	5.75	(1.31)	0.01	(0.95)	5.53	(1.20)	5.74	(1.31)	-0.22	(0.10)
Workers Technicians	1.24	(0.75)	1.45	(0.80)	-0.21***	(0.00)	1.49	(0.87)	1.45	(0.81)	0.04	(0.62)
Observations	2068 (1881 No Abs, 187 Abs)						372 (186 No Abs, 186 Abs)					

Notes: Differences reported as means (No Absences – Absences). p-values from t-tests. Standard deviations (SD) are in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

On the right side of table 2, I provide a similar comparison but using the nearest-neighbor matched sample. I observe differences across observable characteristics in the unmatched sample, but nearest neighbor matching allows me to create a balanced sample with no significant differences between control and treatment groups. I present differences between variables across treatment and control group with the p-value of the t-test in the last column in both tables. Using matching, I address the issue of observable differences in workforce composition in shifts affected or not by middle manager absences.

In table A1 in the online appendix, I present the statistics regarding the various training programs that took place between June 2000 and June 2002 at the Bhilai Rail and Structural Mill. The most frequent training focused on improving productivity by enhancing the production process. Additionally, safety training within the facility and formal certifications were popular among workers. The raw data included many different descriptions of the training programs, which I grouped into 8 main categories based on the available descriptions. For example, I combined training programs like "Enhancing production and dispatch of prime rails," "Increase acceptance of rails," and "Increase dispatch of rails to 1800 t/day" under the category "Improve production process" Similarly, all training aimed at obtaining ISO qualifications was categorized as "Formal certifications." The numbers reported in the table represent the count of individual training programs completed by each worker, reflecting the total number across all workers in the factory.

In figure 1, I illustrate the evolution of production before and after the training implemented in June 2001 for shifts with and without middle manager absences. The graphs plot the three-month averages of rail production for the four quarters before and the four quarters after the training. There is a sharp increase in rail production immediately following the program. Notably, while the increase is around 20 units of output for shifts without absences, it rises to approximately 40 units for shifts affected by manager absences. This is a suggestive evidence that the effect of the training was much larger in shifts were there were less middle managers present on the production line.



(a) Shifts without manager absences (b) Shifts with manager absences

Figure 1: Production over time for shifts with and without manager absences

In Figure A1 of the online appendix, I present the 90-day moving average of the daily average number of production-practice training days attended by workers present on each shift. All training days from 1998 onward are included and any program mentioning production process improvement in its description is considered. The figure shows that such trainings occurred before June 2001, but a sharp increase is observed around that time, coinciding with a production halt and the intensive program I study. Additionally, similar intensive training was not assigned to workers during other periods between June 2000 and June 2002.

In figure 2, I show the 90 days de-trended moving average of manager absences between June 2000 and June 2002. Although it shows a decreasing trend over at the start of the time period considered, there is no discontinuity around the time of the training program. The decreasing trend might be related to the risk of downsizing of the company and a reduction of procurement contracts linked to low output and quality. This reassures to the risk that the results might be affected by a different behavior of managers regarding their absences from work before and after the training program.

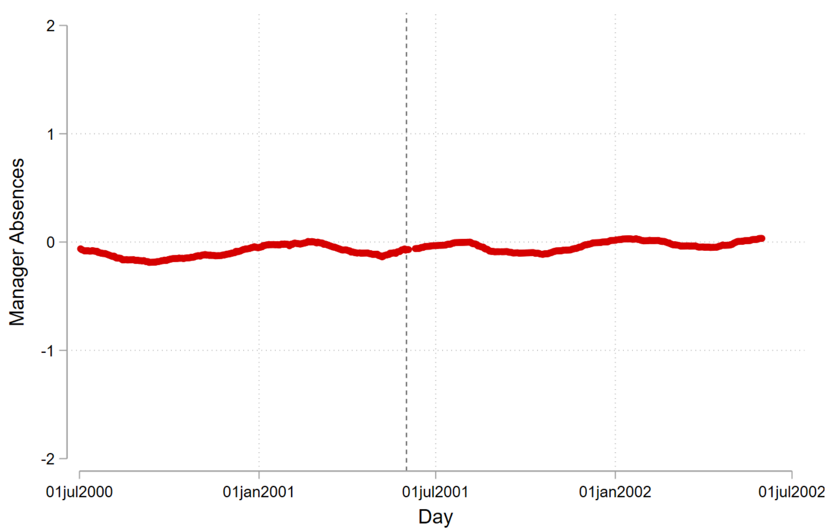


Figure 2: Detrended 90 Days Moving Average Manager Absences

I do not observe any sharp change across the training date that can be considered as a confounding element for the estimation of the effect of the training program. In figure A2 in the online appendix, I show the de-trended 90 days moving average for workers present on the working floor in a shifts. This shows that the workforce did not increase or decrease around the training in June 2001 excluding that the results estimating the effect of training could be driven by changes in the number of workers available.

To conclude, table 2 provides an overview of the training program conducted in June 2001. In panel A of table 2, I focus on operative workers, showing that over 80% of them participated in the training program, while only 41 out of 244 operative workers did not attend any training sessions. A total of 322 workers participated in the program, with most attending for one or two days, and 52 workers attending for three or more days. In panel B of table 2, I present the distribution of attendance days among all individual workers, including those not directly involved in the production line.

Table 2: Training Participation and Attendance

Panel A: Operatives' Participation			
		Frequency	Percent
No participation		41	16.80
Participation		203	83.20
Total		244	100.00
Panel B: Training Attendance (All Workers)			
Days training	Frequency	Percent	Cum.
1	113	35.09	35.09
2	157	48.76	83.85
3	47	14.60	98.45
4+	5	1.55	100.00
Total	322	100.00	

Notes: Panel A reports whether operative workers attended any training. Panel B shows total training days among all workers. Data from administrative records.

7 Empirical Results

In this section, I present the regression results estimating the effect of training on production when managers are absent. I start by presenting the estimates of equation 1 using propensity score weighting. Second, I show the estimates with using weights in the regression. Then, I replicate the same estimates by using nearest neighbor matching and exact matching. To conclude, I estimate the same equation equation excluding shifts with high planned maintenance operation planned and, to conclude, I estimate an event study design. In the next sections, I provide the results of these econometric estimates.

The main identification assumption is based on the fact that the company's structure did not undergo systematic changes before and after the training, with the training program being the only source of variation. One potential concern is that manager absences may have varied across the training period or that workers becoming more independent may have led the firm to adjust the number of workers on the production line.

To address this potential concerns I show that middle manager absences did not vary after the training[8]. Two managers were still required according to the shift organization and, consequently, the number of shifts with less than two middle managers did not change. This point is particularly important: if the training had led to a systematical difference of absences of managers, as might be expected if workers became more autonomous, it could confound the estimation by introducing another source of variation.

I also show that the number of workers present during a shift did not change across training period. I do not observe changes in the workforce as a consequence of the training program that could be another confounding in this setting. Additionally, I use matching on shift-level variables to construct treatment and control groups that are highly similar in terms of observable characteristics, thereby addressing potential differences that could bias the estimates.

Another assumption on which I rely the identification strategy is that the type of production did not change across the training. I do not have information about any change in the type of production like different types of rails of structurals that the company produced differently after the training. I consulted internal reports and the corporate newspaper and they did not mention any change on output produced in that period.

7.1 Regression Results

I present the results of the weighted regressions as my main specification using propensity score weighs to address differences in observable characteristics between shifts with and without manager absences as shown in table 1. I use the method outlined in Section 5 to

[8]See figure 2

estimate the propensity scores and incorporate inverse propensity score weights in the regressions. This weighting approach assigns greater importance to treated observations that closely resemble control observations, and control observations more similar to the treatment group. By doing so, I make use of the available data to reduce the influence of dissimilar observations, ensuring that the estimated effects are not driven by underlying differences between treated and control shifts.

In table 3, I present the regression estimates weighted by inverse propensity scores. Middle manager absences negatively affect production per worker by 17% and reduce the production rate by 0.17 units of output per minute in shifts where rails are produced. Training increases production per worker by 10% and reduces shifts with at least one unexpected delay by 8%, but it does not affect the rolling rate. Therefore the effect of training on production per worker in shifts without manager absences is mostly driven by reduction in unexpected stoppages happening on the production line. I find no effects of training on defective output. Shifts affected by manager absences show further improvements after the training, with output per worker increasing by approximately 18.5%, rolling rate improving by around 0.17[9] output per minute and a further 9.6% decrease in shifts with delays, although this last coefficient is barely not statistically significant.

My findings suggest that the training was effective in raising output and productivity measures, particularly in shifts where managers were absent from the production line. The results in table 7 show that the training significantly reduced unexpected delays, which helped to increase production per worker. In shifts with at least a manager missing, the training improved the number of rails produced per minute, output per worker and further decreased delays. This training, designed to make workers more productive and able in completing their tasks for rail production, not only enhanced production outcomes but also mitigated, and nearly offset, the negative effects of manager absences on production and productivity measures.

[9]22% increase compared to shifts affected by middle manager absences in the pre-training period.

Table 3: Regression Results for Rail Production with Weights

	Rolling Rate	**Log Blooms per Worker**	**Percent Defected**	**Delay**
Abs_{izt}	-0.169***	-0.168**	-0.003**	0.057
	(0.050)	(0.050)	(0.001)	(0.060)
$Post_{izt}$	-0.008	0.106***	-0.001	-0.083*
	(0.020)	(0.030)	(0.001)	(0.030)
$Abs_{izt} * Post_{izt}$	0.169**	0.185*	0.002	-0.096
	(0.050)	(0.080)	(0.001)	(0.070)
N	1397	1397	1397	1397

Note: Regression results on sample of rail shifts between June 2000 and June 2002, weighted using inverse propensity scores procedure explained in section 5. * 10%, ** 5% and * 1% significance level. Equation: $y_{izt} = \beta_0 + \beta_1 Abs + \beta_2 Post + \beta_3 Post * Ab_{izt} + \gamma_z + \tau_t + \eta_i + \theta X_{izt} + \epsilon_{izt}$. γ_z team fixed effect, τ_t month fixed effects, η_i shift fixed effects. First column reports results for output per minute worked. Second column reports results for log output made per worker in a shift. Third column reports results for percentage of defective output. Fourth column reports results for minutes of delay during a shift. Standard errors are clustered at the team by month level and reported in parenthesis.

7.2 Robustness Checks

In table 4, I present the results from the unweighted regression analysis of rail production and the findings reveal that absences have a substantial impact on production outcomes also in this specification. In this specification, absences of managers lead to a reduction in production per worker by 17.6%, and a decrease in the rolling rate, measured as output per minute worked, by 0.1 units. Training proves to be effective in increasing productivity and production outcomes. I estimate a 16% increase in production per worker after the training, and an additional 15% increase in shifts affected by manager absences. With a similar pattern, I estimate that the rolling rate improves by 0.02 units of output per minute during a shift after the training program, with an extra 0.087 unit increase when managers are absent. Training almost offsets the negative effects of the absent manager on these production and productivity outcomes. On top of this, the training program results in a slight reduction in the percentage of defective output and an 8% decrease of shifts affected by unexpected delays, as detailed in Columns 3 and 4. For these two outcomes, there is no significant additional effect of training on shifts impacted by manager absences. The estimated coefficients are similar to the one presented in the main specification.

Then, I use a nearest neighbor matched sample without weighting. First, I estimate the propensity scores as presented in section 6 and in the same way I used for my main specification. Then, I match pairs of observations with similar estimated propensity scores between treatment and control shifts affected or not by manager absences creating a matched sample of shifts producing rails components. Additionally, I matched shifts with manager absences and not within pre or post training periods separately. Finally, I estimate equation 1 on the matched samples.

Table 4: Regression Results for Rail Production

	Rolling Rate	**Log Blooms per Worker**	**Percent Defected**	**Delay**
Abs_{izt}	-0.097***	-0.176***	-0.002	0.074
	(0.028)	(0.051)	(0.003)	(0.051)
$Post_{izt}$	0.020***	0.159***	-0.002**	-0.082**
	(0.005)	(0.022)	(0.001)	(0.033)
$Abs_{izt} * Post_{izt}$	0.087**	0.151*	0.000	-0.040
	(0.028)	(0.063)	(0.003)	(0.071)
N	1590	1590	1590	1590

Note: Regression results on sample of rail shifts between June 2000 and June 2002, non weighted. * 10%, ** 5% and * 1% significance level. Equation: $y_{izt} = \beta_0 + \beta_1 Abs + \beta_2 Post + \beta_3 Post * Ab_{izt} + \gamma_z + \tau_t + \eta_i + \theta X_{izt} + \epsilon_{izt}$. γ_z team fixed effect, τ_t month fixed effects, η_i shift fixed effects. First column reports results for output per minute worked. Second column reports results for log output made per worker in a shift. Third column reports results for percentage of defective output. Fourth column reports results for minutes of delay during a shift. Standard errors are clustered at the team by month level and reported in parenthesis.

I use two different matching methods a nearest neighbor matching and a nearest neighbor plus an exact matching on a variables. For the first, I matched on shifts with closest estimated propensity scores between treatment and control groups. For the second, I use an exact matching on the team identifier so that the matched shifts are constrained to be operated, by construction, by the same team.

In table 5, I present the regression estimates using the nearest neighbor matched sample. These findings confirm the results from table 7. As expected, absences decrease output produced per minute by 0.09 units, per-worker production by 15.5%, and increase shifts affected by unexpected delays. The training shows a positive impact, particularly in shifts affected by manager absences. Although the point estimates are slightly smaller than those from the weighted regression, they are very close to those obtained from the non-weighted regression. Overall these estimates confirm the findings reported in table 3. I find that training increased productivity by 0.045 units of output produced per minute and production per worker by around 25%. Training, in shifts affected by manager absences, increased rolling rate by a further 0.087 units per minute worked and output per worker by and additional 16%.

Table 5: Regression Results for Rail Production NNM

	Rolling Rate	**Log Blooms per Worker**	**Percent Defected**	**Delay**
Abs_{izt}	-0.090**	-0.155*	-0.002	0.135*
	(0.030)	(0.060)	(0.001)	(0.060)
$Post_{izt}$	0.045*	0.259***	-0.001	-0.049
	(0.020)	(0.060)	(0.001)	(0.050)
$Abs_{izt} * Post_{izt}$	0.087**	0.159*	-0.001	-0.088
	(0.030)	(0.080)	(0.001)	(0.070)
N	292	292	292	292

Note: Regression results on nearest neighbor matched sample of rail shifts between June 2000 and June 2002. * 10%, ** 5% and * 1% significance level. Equation: $y_{izt} = \beta_0 + \beta_1 Abs + \beta_2 Post + \beta_3 Post * Ab_{izt} + \gamma_z + \tau_t + \eta_i + \theta X_{izt} + \epsilon_{izt}$. γ_z team fixed effect, τ_t month fixed effects, η_i shift fixed effects. First column reports results for output per minute worked. Second column reports results for log output made per worker in a shift. Third column reports results for percentage of defective output. Fourth column reports results for minutes of delay during a shift. Standard errors are clustered at the team by month level and reported in parenthesis.

In table A2 in the online appendix, I present regression run on a nearest neighbor matched sample with the condition that the pairs of treated and control shifts are operated by the same team. I find that absences of manager decrease the rolling rate by 0.085 units per minutes worked, output per worker by 25.5%, I find that training increases output and that the effect of training is larger in shifts affected by manager absences. I find that in these shifts, the rolling rate increases by an additional 0.079 units per minute and output per worker by 24.7%. The estimates are similar to the findings using the nearest neighbor matched sample reported in table 5 and support the findings from main specification in table 3 although, in both cases, the effect of training on rolling rate in shifts affected by manager absences is smaller compared to the main specification. Again, I find the training to be effective in increasing productivity also in shifts not affected by middle manager absences.

I estimate the effect of training excluding shifts where more than half of the time was dedicated to planned maintenance including propensity score weighting as in the main specification. If time of planned maintenance changed across the training period, the estimates of the main regression could be bias. By excluding shifts with high maintenance I aim to mitigate this possible concern. I show the estimated results in table A3 in the appendix, I find that absences decrease rolling rate, percentage of defected output and output per worker with a similar magnitude compared to the main estimates presented in table 3. Training decreases shifts affected by unexpected delays by 11% and, consequently, there is an increase of 8% in output per worker. As estimated in the other specifications, I find that the training mitigates the effects of manager absences by further increasing productivity and production per worker when shifts are affected by manager absences in the post training period.

7.3 Event Study Design

To conclude, I estimate an event study design to show how output changes when a team is affected during a shift by a manager absences. With this model I show the dynamic effect on output of a middle manager absences in the days before, during and after the absences. The regression equation is as follows,

$$Y_{izt} = \beta_0 + \sum_{k=-2,k\neq-1}^{k=2} \phi_k D_{izt}^k + \phi^{pb} D_{izt}^{pb} + \gamma_z + \tau_t + \eta_i + \theta X_{izt} + \epsilon_{izt} \qquad (2)$$

Y_{izt} is level of output produced in shift i by team z in month t. D_{izt}^k are the event study variables. D_{izt}^{-2} is equal to 1 for shifts occurring 3 or 4 days before a manager absence and zero otherwise. I define the other event study variables similarly. D_{izt}^0 defines shifts affected by a manager absence. D_{izt}^1 defines shifts occurring 1 or 2 days after a manager absence. D_{izt}^2 defines shifts occurring 3 or 4 days after a manager absence. D_{izt}^{pb} is a catch-all dummy variable that indicates all shifts occurring 5 days or more before and after a middle manager absence. The baseline in this event study design is shifts taking place 1 or 2 days before the manager absence. I assume that the parallel trend assumption holds and I support this claim by showing no anticipatory effects in the estimates. I cluster standard errors at the team by month level.

I extend equation 1 to include event study variables to capture possible anticipating or permanent effect. In the event study variables, I pool together 2 days instead of 1 because the number of observations is not high and otherwise parameters would not be precisely estimated. γ_z, τ_t and η_i are team, month and shift fixed effects. X_{izt} is a vector of time varying team and shift characteristics such as people working in each role during a shift and average age of the team working during a shift. I run this equation pre and post training to understand how the effect on output and its dynamics changes. I use output in levels to compare the output loss between pre and post training periods. I cluster standard errors at the team by month level. I weight the regression using propensity score weights and I estimate this model for shifts taking place one year before and after the training, similarly to what has been done in estimating equation 1.

I find that the effect of absences on production is substantial in the pre-treatment period but negligible thereafter. In figure 3, I present the event-study coefficients for the days surrounding a manager's absence for the pre and post training period. In green, I estimate that in shifts affected by absences, output decreases by approximately 50 units compared to pre-absence shift output. I find no evidence of either anticipatory effects before the absence or persistent effects afterward. In orange, I report the corresponding regression results for the post-training period. Consistent with the findings in the previous section, I find that manager absences have no significant impact on production. Using a back-of-the-envelope calculation, based on the fact that there were 124 shifts affected by absences in the year prior to training, I find that manager absences led to a loss of more than 6000 units of output, relative to a total annual production of 162.000 units. This corresponds to a decline of about 3.5%, compared to the post-training environment where the effect of manager absences is negligible.

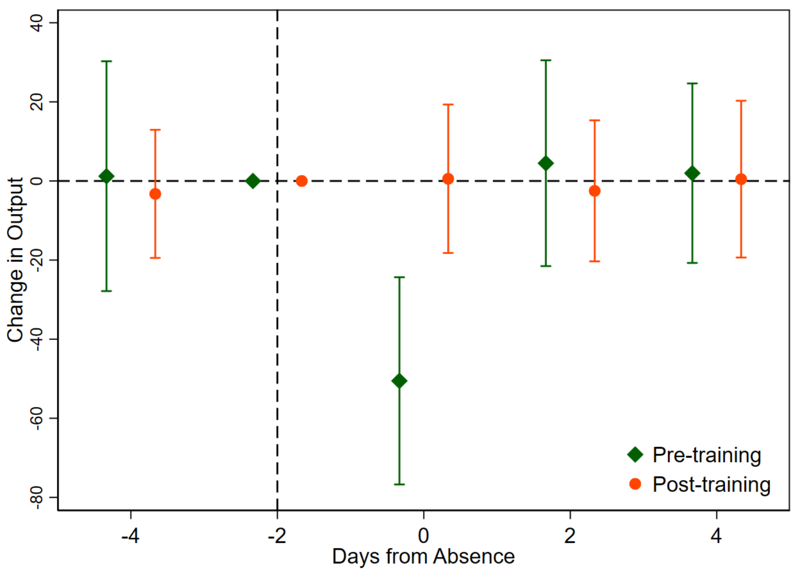


Figure 3: Event Study Design

Notes: Regression equation is $Y_{izt} = \beta_0 + \sum_{k=-2,k\neq-1}^{k=2} \phi_k D_{izt}^{k} + \phi^{pb} D_{izt}^{pb} + \gamma_z + \tau_t + \eta_i + \theta X_{izt} + \epsilon_{izt}$. The figure presents the coefficient estimates of γ_t from equation 2 for pre and post training periods. I show the 95% confidence intervals. The method used to estimate the event study model is an Ordinary Least Squares (OLS). Standard errors are clustered at the team by month level. Baseline used is one-period before treatment. Treatment is defined as a team having a manager absence at $t = 0$. I use team, shift and month fixed effects. Each lead and lag in the event study design here reported contains two days. Standard errors are clustered at the team by month level.

8 Discussion of the Results

The results from the main specification show that the training increased production of rails, as I show in figure 6, by reducing unexpected delays and by mitigating the effects of manager absenteeism on productivity. The training, which aimed to improve production practices across the workforce, decreased the likelihood of a shift being affected by unexpected delays between 4% and 8% across the different specifications used, boosted production per worker by around 10% and 20% and increased output produced per minute, in most of the regressions estimated, between 1% and 4%. I find no effect on defective output.

The training had a significant effect on mitigating the effect of manager absences. In shifts affected by middle manager absences, the training boosted productivity, measured as output per minute worked, by an additional 0.17 units and total production per worker by an additional 18.5%, according to the main specification. I find similar results in the other specifications as well, with production rate increasing between 0.08 and 0.2 units per minute and production per worker increasing between 15% to 20%. I do not find such an effect of training on shifts affected by middle manager absences for other variables as unexpected delays or percentage of defective output.

I find that manager absences have negative effects on production and productivity outcomes. They affect production by reducing the rolling rate by 0.17 units of output per minute and production per worker by 17%. I find no effect of manager absences on defective output while I estimate positive but, in three out of four specification, not significant effects of manager absences on the percentage of shifts affected by unexpected delays. Estimations are similar across different specifications in the various robustness checks performed, proving that manager absences in a context with a low trained workforce have a large impact on production.

The training improved production mainly through two channels: reduced stoppages of the production line and increased productivity in shifts with absences of middle managers. Before the training, workers relied heavily on middle managers to complete their tasks, so a manager's absence caused significant disruptions during shifts. However, after the training, which had the goal to improve production practices, the importance of middle managers diminished. This is evidenced by the fact that the training almost fully offset the negative effects of manager absences on productivity, measured as output per minute worked. By reducing the impact of manager absenteeism, the factory was able to increase total output. This is an important and generalizable finding also for other similar context where workforce is predominately low skilled and with low training Sharma (2024); Hajela (2012)

The effect of the training on structural component production is negligible, as shown in the appendix tables A4 to A7 and in figure A3. I estimate a decline in productivity and output per worker after the training, likely due to the reduced focus on structural component production after 2001. The influence of manager absences is less pronounced in structural component production, as the process is simpler and managers played a less critical role even before the training. Since the program targeted practices specific to rail production, it did not produce positive effects on shifts devoted to structural components, as confirmed by estimates across different specifications. Overall, the training did not increase output and productivity in shifts dedicated to the production of structural components.

Estimating the event-study model, I find again large negative effects of manager absences in the pre-training year. There is no evidence of anticipatory or persistent effects on shifts contiguous to those affected by manager absences. I estimate, in the pre-training period, that middle manager absences reduce output by about 50 units per shift compared to pre-absence shifts, whereas I do not find such effect in the period after the training program ended. A back-of-the-envelope calculation indicates that, in the year before training, middle manager absences reduced annual output by approximately 3.5% compared to the post-training environment where the effect of manager absences is not statistically significant.

9 Conclusion

In this paper, I examined the effects of a training program designed to enhance the productivity of low-trained and non-specialized operative workers. The program aimed to improve production outcomes following a new procurement agreement with the Indian Ministry of Railways and before any new physical capital investments were made. The firm operated within a highly vertical structure, and the goal of the training program was to improve production practices of operative workers and their ability of performing tasks on the production line without help from middle managers, thereby reducing time-wasting interactions between these two groups that previously slowed down the production process.

I find the program to be successful in improving production outcomes, particularly in shifts where middle managers were absent. The training increased production and reduced delays. Moreover, the program also proved to be effective in mitigating the negative impact of manager absences on production. In fact, productivity, measured as output per minute worked, increased exclusively in shifts where at least a manager was absent.

I contribute to the literature regarding on-the-job training by providing evidence on how a training program, aimed at reducing organizational frictions, can increase output and improve productivity. Before the training, operative workers were highly reliant on their middle managers, leading to significant time lost as they had to assist them. After training program, I find fewer production delays, increased productivity and higher total output produced, particularly when managers were absent. While previous literature has examined the effects of training programs on production, it has not explored how such programs can mitigate the impact of absenteeism on output and productivity (Niati et al., 2021; Elnaga and Imran, 2013; De Grip and Sauermann, 2012; Ballot et al., 2006). Moreover, I contribute to the literature on absenteeism by estimating the effects of manager absences in production in a context of a firm with a low educated and low trained workforce.

The findings of this paper may be generalizable to similar settings where workers have limited training and depend on supervisors to complete their tasks. Training programs designed to improve production practices in these contexts could yield benefits comparable to those observed at the Bhilai Rail and Structural Mill. However, the training implemented in this case was neither standardized like the programs developed for ISO certifications nor documented in sufficient detail to be precisely and directly replicated elsewhere. Nevertheless, anecdotal evidence suggests that the program was effective in diffusing knowledge of correct production practices across the workforce, whereas previously this knowledge had been concentrated among middle managers. Therefore, similar training initiatives may reduce reliance of workers on their supervisors and help mitigate the negative impact of absenteeism in similar contexts.

There are several avenues for future research on how training programs can enhance worker independence and improve firm outcomes. Although I estimate the effects of a training program aimed at increasing ability of workers to perform tasks by their own, this study faced certain limitations due to data constraints, which future research can address. First, I lack direct measures of worker independence, which could be gathered in future studies through survey data not available in my current setting. Second, future research could improve on this paper by identifying the specific causes of absences, rather than relying on matching shifts affected by absences with those sharing similar observable characteristics. Third, similar studies could be replicated in other contexts to examine how training programs may yield different effects across organizational structures, countries, educational backgrounds, cultural settings and industrial sectors. Fourth, additional studies should be performed to understand which specific type of training are effective.

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