NBER WORKING PAPER SERIES

MANAGEMENT AND SHOCKS TO WORKER PRODUCTIVITY

Achyuta Adhvaryu
Namrata Kala
Anant Nyshadham

Working Paper 25865
http://www.nber.org/papers/w25865

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2019

We thank Hunt Allcott, Manuela Angelucci, Nick Bloom, Dave Donaldson, Pascaline Dupas, Josh Graff Zivin, Ben Jones, Rocco Macchiavello, Aprajit Mahajan, Grant Miller, Melanie Morten, Dilip Mookherjee, Antoinette Schoar, John Strauss,Tavneet Suri, Chris Woodruff, Dean Yang, and seminar participants at USC, Stanford, Michigan, UIUC, Penn, Brown, UCSD, BC, BREAD, PEDL, Warwick, and the NBER for comments and suggestions. We are incredibly thankful to Anant Ahuja, Chitra Ramdas, Shridatta Veera, Manju Rajesh, Raghuram Nayaka, Sudhakar Bheemarao, Paul Ouseph, and Subhash Tiwari for their coordination, enthusiasm, support, and guidance. This research has benefited from support by the Private Enterprise Development in Low-Income Countries (PEDL) initiative. Thanks to Tushar Bharati and Robert Fletcher for valuable research assistance. Adhvaryu gratefully acknowledges funding from the NIH/NICHD (5K01HD071949). All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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May 2019
JEL No. L23,M11,M54

ABSTRACT

The assignment of workers to tasks is an important feature of the organization of production within firms. We study how task allocation across workers changes in response to productivity shocks. Pairing hourly productivity data from a ready-made garments firm with granular data on exposure to particulate matter pollution, we show that productivity suffers as a result of pollution shocks; this effect is heterogeneous across workers and tasks. Managers respond by reassigning workers to tasks in which they perform better on average during shocks. This response is larger for managers who we identify, via survey-based measurement, as exhibiting greater managerial attention, and these same managers are also the ones who are most able to mitigate resulting productivity declines.

Achyuta Adhvaryu
Ross School of Business
University of Michigan
701 Tappan Street
Ann Arbor, MI 48109
and NBER
adhvaryu@umich.edu

Anant Nyshadham
Department of Economics
Boston College
Maloney Hall, 324
Chestnut Hill, MA 02467
and NBER
nyshadha@bc.edu

Namrata Kala
MIT Sloan School of Management
100 Main Street, E62-517
Cambridge, MA 02142
and NBER
kala@mit.edu

1 Introduction

The organization of production within firms is of foundational importance in economics (Lazear and Oyer, 2007; Lazear and Shaw, 2007). A crucial feature of this organization is the allocation of workers or teams to tasks (Costa, 1988; Rosen, 1982). For example, it may be optimal for managers to assign their most talented workers to the hardest or most important projects; it may also be optimal to shift task allocations when the skills or capabilities of team members change. This process of managing task assignments is likely to a play critical role in the success or failure of the firm (Gibbons and Waldman, 2004; Holmstrom and Tirole, 1989; Kremer, 1993). While this idea is well developed in theory, actually observing the behavior of managers in this regard – and then linking it to specific shocks that might generate a need for task reallocation – is inherently difficult, and thus has received limited attention.

In this study, we pair detailed data on worker and line productivity, task assignments, and managerial characteristics with highly granular air pollution measurements in a ready-made garments firm in India. Particulate matter pollution is an important public health concern in many urban environments in low-income countries (Pope and Dockery, 2006). Short-term exposure to high pollution levels generates temporary reductions in physical and cognitive functioning (Brunekreef and Holgate, 2002), which in turn affects worker productivity (Chang et al., 2014). Moreover, there is likely substantial heterogeneity in the way in which workers are affected by a given pollution shock, depending, for example, on their baseline respiratory health, or their exertion levels with respect to the workplace tasks to which they have been assigned (Schwela, 2000).

We begin by showing evidence for this relationship in our study context. We show that fairly large particulate matter pollution shocks are commonplace, and that worker- as well as line-level productivity suffers during these shocks. The relationship between air pollution and productivity is approximately linear, small, and precisely estimated: a one standard deviation increase in pollution decreases efficiency (a standardized productivity measure in the ready-made garments sector) by half a point, which is about one percent of mean productivity. Event study analysis confirms that large pollution shocks have immediate effects on worker productivity. Impacts are about 60 percent larger for workers performing complex tasks, and about 35 percent larger for older workers.

Managers who notice productivity declines in particular workers may find it optimal to reassign these workers to tasks, in a way that reflects the limited ability of affected workers to exert effort in their assigned jobs. In line with this, we find that the probability of task reallocation on production lines increases by about 3 percentage points (about 7 percent of mean reallocation) following a one standard deviation increase in pollution. This effect masks nuanced heterogeneity of impacts on task reallocation. Specifically, we show that during pollution shocks, workers are actually allocated *away* from the tasks that they are (idiosyncratically) "best" at in non-shock periods. This is because pollution shocks affect workers' performance most for exactly these baseline high-efficiency tasks. That is, we show that the rank order of operations at which a particular worker is most productive changes as pollution rises, such that the tasks at which a worker has high potential for productivity during low pollution times fall in rank as pollution rises relative to tasks at which they are ordinarily less productive. Interestingly, depending on the frequency of productivity shocks, it may thus be optimal for managers to assign workers to tasks for which they are not particularly well-suited in the absence of shocks.

Finally, using detailed survey data on managerial quality, we show that managers who report investing more effort in monitoring their lines and more actively managing day-to-day personnel decisions are indeed the ones who reassign workers more intensively in response to pollution shocks. These same managers (i.e., those who are not prone to inattention) are most able to mitigate the impacts of pollution shocks on line productivity.

Our study contributes to the understanding of the organization of production within firms. Assigning workers to tasks optimally based on their relative advantages is a key lever through which good management drives productivity, and is critical to the overall success of firms. While much theory has been brought to bear on this topic (Costa, 1988; Holmstrom and Tirole, 1989; Lazear and Oyer, 2007), the empirical literature on evaluating the importance of task assignment within firms is relatively recent (Amodio and Martinez-Carrasco, 2018; Bandiera et al., 2007, 2009; Burgess et al., 2010; Friebel et al., 2017; Hjort, 2014). To the best of our knowledge, this study is the first to examine how idiosyncratic productivity shocks affect this task allocation process. One important finding that emerges from this investigation is that worker-specific productivity orderings of tasks may change in response to shocks, such that it may be optimal to reassign workers away from their "best" tasks during shocks.

We also contribute to the literature on management and productivity. Managerial quality is highly associated with firm productivity (Adhvaryu, 2018; Adhvaryu et al., 2018; Bloom and Reenen, 2011; Bloom and Van Reenen, 2007; McKenzie and Woodruff, 2016), including in experimental studies (Bloom et al., 2013, 2018b; Karlan et al., 2015; McKenzie and Woodruff, 2013). A few recent studies have sought to understand which particular practices matter most, though much work remains to be done in this regard (Bandiera et al., 2017; Bloom et al., 2018a, 2016; Campos et al., 2017). We add to this recent strand of work by showing one mechanism through which two important dimensions of managerial quality – monitoring (Bloom et al., 2012; Halac and Prat, 2016) and active personnel management (Aghion et al., 2017; Bresnahan et al., 2002) – generate productivity impacts by mitigating the negative effects of shocks.

The rest of the paper is organized as follows. Section 2 discusses the readymade garments production process, and reviews the evidence on the physiological impacts of pollution exposure. Section 3 discusses our data sources and the construction of key variables. Section 4 describes our empirical strategy. Section 5 reports the results, and section 6 concludes.

2 Background

In this section, we discuss the garment sector in India, key elements of the garment production process including the role of supervisors in determining productivity, and the physiological impacts of air pollution exposure.

2.1 The Indian Ready-made Garments Sector

Global apparel is one of the largest export sectors in the world, and vitally important for economic growth in developing countries (Staritz, 2010). India is the world's second largest producer of textile and garments, with export value totaling $10.7 billion in 2009-2010. The steady transition of employment shares in much of the developing world, from rural agricultural self-employment to urban wage labor, is manifest in the readymade garments industry, which mainly employs relatively young unskilled/semi-skilled workers, many of them female (Heath and Mobarak, 2015; Staritz, 2010; World Bank, 2012). Our research partner, Shahi Exports, Pvt. Ltd., is the largest exporter of ready-made garments in India.

2.2 The Garment Production Process

There are three broad stages of garment production: cutting, sewing, and finishing. In this study, we focus on sewing for three reasons. First, sewing makes up roughly 80% of the factory's total employment. Second, a standardized measure of output is recorded for each worker in each hour on the sewing floor. Third, the number of lines, and hence supervisors, is sufficiently large, and the mapping of supervisors to workers and workers to tasks is sufficiently dynamic (yet clearly observable), to allow for the study of the interaction between supervisors and workers, and the assignment of workers to tasks.

Garments in this factory setting are sewn in production lines consisting of roughly 65-70 workers (depending on the particular features of the style) arranged in sequence and grouped in terms of segments of the garment (e.g., sleeve, collar, etc.). Two-thirds to three-quarters of the workers on the line are machine operators completing production tasks, while the remainder are helpers who are responsible for supporting tasks such as folding, aligning and feeding. Each line produces a single style of garment at a time (i.e., color and size will vary but the design of the style will be the same for every garment produced by that line until the sales order for that garment is met).[1] Bundles of materials for roughly 10 or 20 garments will be fed to each segment of the line. Completed sections of garments pass between machine operators, are attached to each other in additional operations along the way, and emerge at the end of the line as a completed garment. These completed garments are then transferred to the finishing floor.

2.3 Task Assignment and the Role of Supervisors

On the sewing floor, line supervisors play several important roles. First, due to absenteeism among workers and the frequently changing demand for skills and efficiency derived from variation in garment complexity, order sizes, and delivery dates and production timelines, the supervisors of each line must adjust the worker composition of the line to optimize garment-specific productivity subject to continually evolving manpower constraints.

Given a line composition, the supervisor assigns each worker to a task or machine operation according to the perceived skill and speed of the worker and the complexity of the task or operation. Through the course of the production day, one of the main responsibilities of supervisors is to adjust this initial worker-task match to continually optimize performance based on worker effort, shocks to capital, and the like. These adjustments, termed "line-balancing," involve switching the tasks to which workers are assigned, or increasing the number of workers on a particular operation to shuffle more efficient workers to harder tasks. Given the complex interrelationships between the productivity of

[1] In general, we describe here the process for woven garments; however, the steps are quite similar for knits and bottoms (shorts and pants), with varying number and complexity of operations. Even within wovens, the production process can vary by style or factory. The factory we are studying is a predominantly woven factory, and therefore, will follow the process outlined here closely.

workers on a given line, as well as the contribution of each worker's productivity to the total productivity of the line (which is of course the ultimate object of concern for management), "line-balancing" is perhaps the most important mechanism by which factory management can respond to worker-specific shocks, and is, therefore, an important determinant of productivity on the sewing floor.

2.4 Physiology of the Pollution-Productivity Gradient

A large body of work connects particulate matter (PM) pollution to a host of morbidity and mortality impacts. Bell et al. (2004); Dockery and Pope (1994); Pope et al. (1999); Pope and Dockery (2006) provide comprehensive literature reviews. There are three main categories of particulate matter based on aerodynamic diameter range: coarse (greater than 2.5 micrometers (μm)), fine (less than or equal to 2.5 μm), and ultra-fine ($<$0.1 μm). The focus in this study is on the second category, fine particulate matter. Fine particulate matter has been shown to have the largest health impacts of the three, due primarily to the following features: relative to larger particulates, they can be breathed more deeply (Bell et al., 2004), remain suspended for a longer time and travel longer distances (Wilson and Suh, 1997), have a more harmful chemical composition, and penetrate indoor environments more easily (Pope and Dockery, 2006).

Both long- and short-term exposures to particulate matter have impacts on health. Long-term exposures have been linked to a variety of impacts, including mortality (see review articles above), usually via elevated risk of cardiovascular events and chronic inflammatory lung injury (Souza et al., 1998), which adversely affects the respiratory tract. Evidence form laboratory experiments confirm that short-term exposures also cause elevated health risks. For instance, studies that have exposed healthy human subjects to fine particulate matter for short periods in concentrations currently found in polluted urban environments in the laboratory find evidence of adverse cardiovascular effects (Mills et al., 2005), as well as acute vasoconstriction, which may also increase the probability of cardiac events (Brook et al., 2002). Thus, both short- and long-term exposures to fine particulates impairs cardiac and respiratory functioning in otherwise healthy adults.

3 Data

3.1 Pollution Data

The air pollution data used in this study were collected from August 2013 to May 2014 using five particulate matter (PM) monitors positioned at different locations across the two sewing floors of the garment factory under study.[2] Two monitors were placed on the first floor on which lines 1 through 9 (along with an occasional line 10) are located; the remaining three monitors were placed on the second floor on which lines 11 through 17 are located. We split lines into segments and match workers in a given hour to the monitor closest to their position on the floor given which segment of the line they occupied.[3] This allows us to measure impacts using fluctuations in exposures to PM levels that vary at the line segment by hour level with sufficient variation across hours of the day for each worker and across workers positioned on different segments of different lines within an hour. We document the variation in worker-level PM exposures below.

The monitors were calibrated to collect two distinct counts of particulates: 1) those between 0.5-2.5 microns in diameter (fine particulates), and 2) those between 2.5 and 10 microns in diameter (coarse particulates). In the analysis that follows, we focus on the impacts of fine PM on efficiency controlling for coarse PM. We do so because fine PM is unlikely to be produced by the garment production activities on the sewing floor, but rather is due to ambient air pollution, namely industrial combustion and automobile exhaust. On the other hand, coarse PM is at least in part produced by the garment production process and could therefore exhibit reverse causality. Lastly, as documented above, studies from environmental and medical literatures suggest that fine PM is the more impactful of the two particulate matter types due to its ability to accumulate in the lungs and restrict respiration.

We can validate the exogeneity of fine PM levels with respect to work outcomes by studying whether fine PM levels decay at the end of the work day and work week when production stops, and how this decay compares to coarse PM fluctuations, which we hypothesize are endogenous to production. Figures 1A and 1B show that while coarse PM is elevated during work days (non-Sundays) and work hours, fine PM peaks during commute times just before and after working hours. Note in

[2]The monitors used were custom calibrated particulate matter count monitors from the Dylos Corporation.

[3]Missing observations seem to be attributable to idiosyncratic monitor crashes and reboots, as it is rare for more than one monitor to have missing measures at the same time. To avoid dropping the worker hour productivity observations for those segments of the lines matched to a monitor with a missing observation, we impute the missing pollution reading as the mean of the pollution exposure of the remaining segments of the line. This imputation applies to roughly 13% of the worker-hour observations used in the analysis. The results are robust to omitting these observations for which pollution measures are missing.

Figure 1A: Daily PM

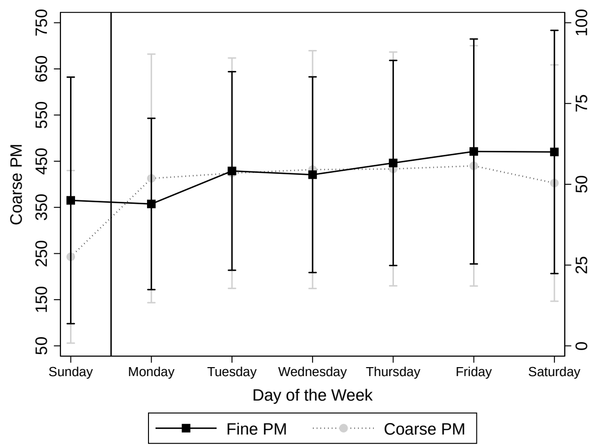
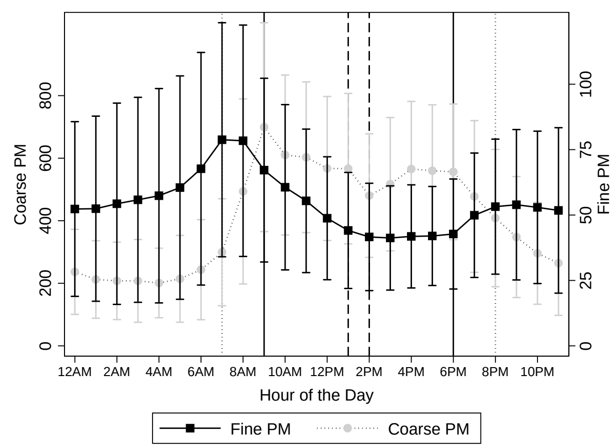


Figure 1B: Hourly PM



Figures 1A and 1B depict mean of fine and coarse PM levels across days of the week (1A) and hours of the day (1B). Vertical line denotes start of production week in Figure 1A. In Figure 1B, vertical solid lines denote start and end of production day; dashed lines denote lunch hour; and dotted lines commuting hours.

particular that coarse PM drops sharply during the lunch hour while fine PM appears smooth.[4]

3.1.1 Fine Particulates (PM 2.5)

As shown in Figures 1A and 1B, fine PM levels vary systematically by day of week and hour of the day. Specifically, fine PM levels tend to be highest on average later in the week and at the beginning of the production day. These patterns likely reflect automobile traffic patterns in addition to the burning of carbon-based fuels for industrial energy demand. Accordingly, our analysis will net out these systematic patterns across days of the week and hours of the day (as well as months of the year). Additionally, Figures 1A and 1B show that indeed within hour of day and day of week a great deal of variation in fine PM realizations exists from which to identify the impacts of fine PM levels on productivity.

Figure 2 shows the degree to which fine PM exposures vary at the worker hour level, after netting out any systematic variation in fine PM levels across months, days of the week, and hours of the day. We present the distribution across days of the proportion of worker-hour observations exhibiting a worker-time-specific PM shock (a level of fine PM 1 SD above the mean of fine PM for that worker at the same hour of day, day of week, and month of year). The distribution shows that on roughly 5% of

[4]Lastly, it is clear that to the degree that fine PM is in fact at all produced by the manufacturing process, this reverse causality would, if anything, bias estimates of the *negative* impact of fine PM exposure on worker productivity towards zero.

Figure 2

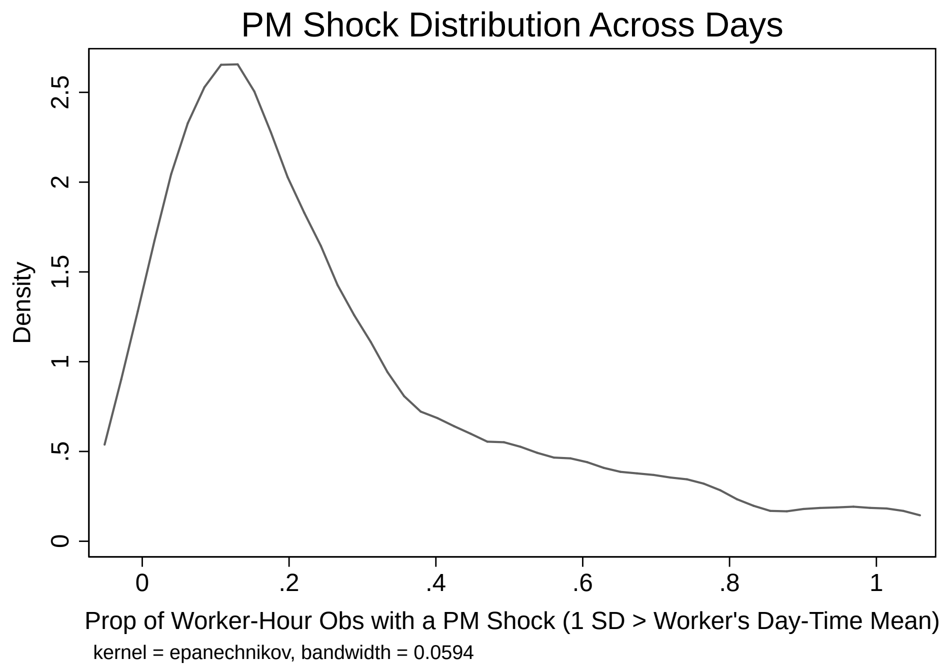


Figure 2 depicts the distribution of the proportion of worker-hour observations in a day exhibiting a PM shock across days. A PM shock here is defined as a level of fine PM 1 SD above the mean of fine PM for that worker at the same hour of day, day of week, and month of year.

days no workers will experience such a shock, but on most days between 0 and 40% of worker-hour observations will exhibit such a shock and as many 80% of workers on some days will face such a shock at some point during the day.

3.2 Production Data

Production data were collected using tablet computers assigned to each production line on the sewing floor. On each line for each hour, the worker, operation, target, and output was recorded.

3.2.1 Productivity

The key measure of worker and line productivity we study below is efficiency. At the worker-hour level, the number of garments that passed a worker's station by the end of that production hour is recorded. For example, if the worker's operation were the sewing of plackets onto shirt fronts, the number of shirt fronts that had plackets attached by the end of a given production hour would be recorded as that worker's "pieces produced."

Efficiency is calculated as pieces produced divided by the target quantity of pieces per unit time (in this case, hour). The target quantity for a given garment is calculated using a measure of garment complexity called the standard allowable minute (SAM). SAM is defined as the number of minutes that should be required for a single garment of a particular style to be produced.[5] That is, a garment style with a SAM of 30 is deemed to take 30 minutes to produce one complete garment. The complete set of operations required to produce this garment is then subdivided across the number of machines on the line (and operators, as all operations are 1 person to machine). If there are, for example, 60 machines/operators on the lines, the SAM of each operation will be around .5.[6] The target quantity for a given unit of time for a worker completing a particular operation on a line producing a particular style is then calculated as the unit of time in minutes divided by the SAM. That is, the target quantity to be produced by a worker in an hour for an operation with a SAM of .5 will be $60/.5 = 120$. If a worker completed the operation 60 times in a given hour, the worker's recorded efficiency for that hour would then be $60/120 = 50\%$.

In order to calculate line-level hourly production from these worker-hour observations, we average across the efficiency of each worker on a production line in a given production hour. This is the most appropriate measure in that it most correctly accounts for partially completed garments at stations along the line in a given hour. Figure 3 shows that line-hour productivity varies a great deal: on a given hour a line might average as little as 20% or as much as 80% efficiency, with the mean line hourly efficiency falling around 50%.

3.2.2 Task Reallocation

The other primary outcome we analyze is a dummy for any task reallocation on the line. Specifically, we first define "task reallocation" as the reassignment of a worker to a different operation from the operation she was doing in the last production hour. That is, if a worker is doing a different operation this hour than last, we code the task reallocation dummy variable as a 1, and code a 0 if they are doing the same operation as in the last hour.[7]

We then construct the line-level task reallocation measure we use in the analysis from these worker-

[5] SAM, as the name denotes, is standardized across the global garment industry and is drawn from an industrial engineering database.

[6] The mean of SAM across worker hourly observations is .62 and its standard deviation is .20.

[7] We ignore operation changes across days, as well as reassignment of workers across lines, as these are primarily driven by manpower fluctuations rather than worker-specific productivity shocks like those we study here.

Figure 3

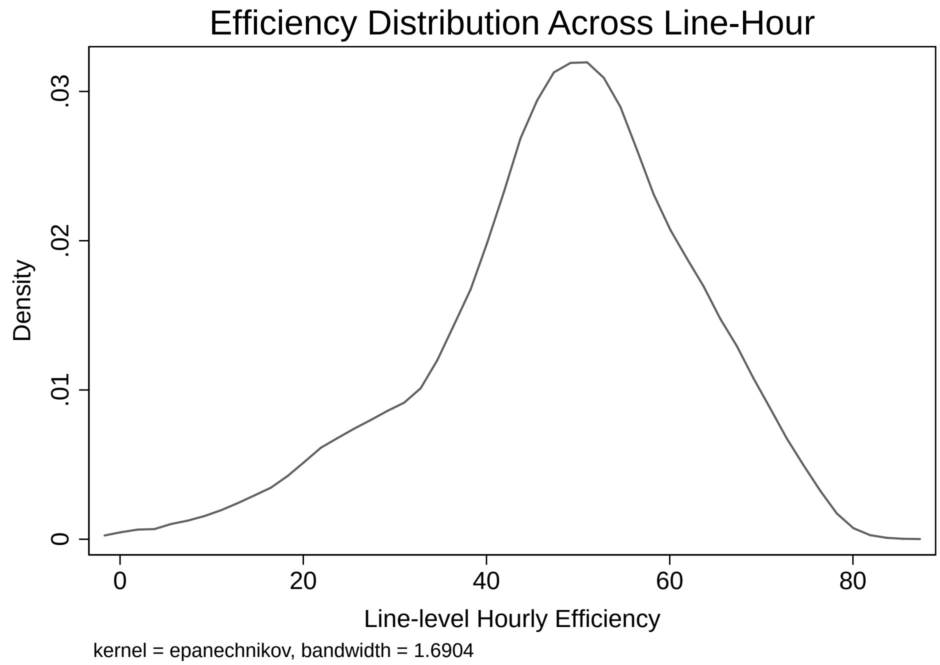


Figure 3 depicts the line-hour distribution of efficiency, showing that on a given hour a line might average as little as below 20% efficiency or as much as 80% efficiency, with the mean line-hourly efficiency falling around 50%.

hour task reallocation measures. *Any Task Reallocation* is a binary variable taking the value 1 if any worker on a line has been moved to a different operation this hour than the operation they were doing last production hour, and 0 otherwise. That is, it is the maximum value across workers on the line of the worker-hour task reallocation measure discussed above. Figure 4 depicts the distribution for the proportion of lines performing any task reallocation within the day. On a given day as few as 0 lines might reallocate at least one worker to a different task or all the lines might reallocate at least one worker to a different task. On average, roughly 60% of lines will reallocate at least one worker to a different task at some point during the day.

3.3 Management Survey Data

In order to assess the degree to which managers exhibiting greater attention to these productivity shocks respond more effectively, we surveyed production line supervisors in the factory. We drew from several sources to construct the management questionnaire, in particular borrowing from Bloom and Van Reenen (2010) to construct instruments measuring management practices, skills, and styles.

Figure 4

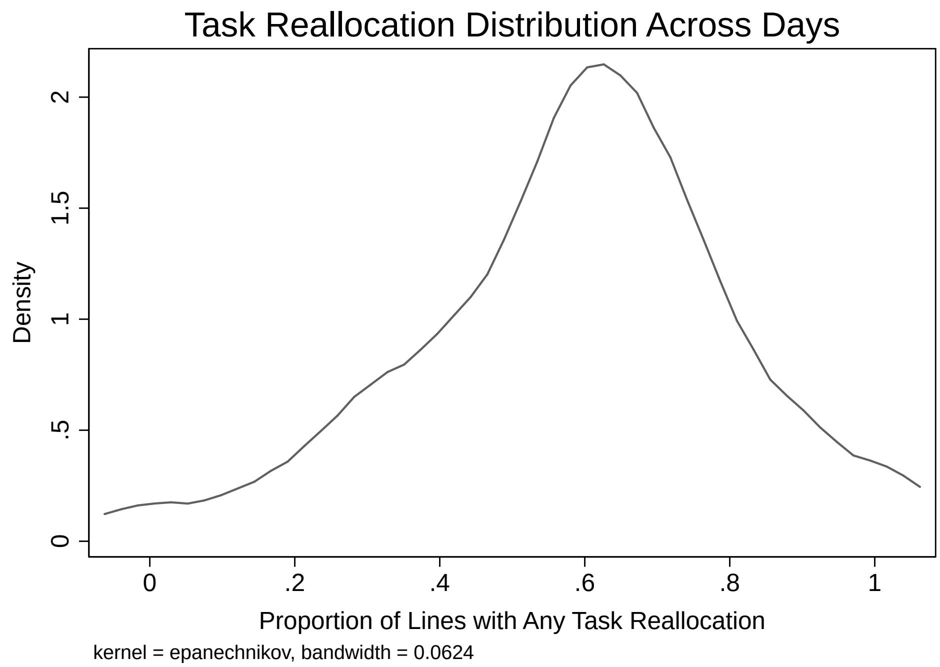


Figure 4 depicts the distribution for the proportion of lines performing any task reallocation within the day.

We investigate the degree to which supervisors' responses to shocks to worker productivity, and the resulting losses, vary by their attention. To do so, we use the two survey measures identified as most informative of managerial attention: monitoring index and active personnel management index.[8]

Monitoring Index is constructed from a question which asks the frequency at which a manager makes rounds of the lines to check for production issues or imbalances. The response took 7 possible values ranging from less than once a day to every 10 min or more. We first simply normalize this categorical variable to generate an index at the individual supervisor level. There are between 1 and 3 supervisors assigned permanently to each line. These supervisors are not necessarily responsible for subsets of workers or operations, but are collectively responsible for the total line. Accordingly, the responses are then averaged across all supervisors assigned to the line. The resulting variable has 4 possible values across line in our sample corresponding to an average across the lines supervisors of rounding at most once a day, less than once per hour, once or twice per hour, more than twice per hour. Figure 5 shows that indeed managers reporting a higher frequency of monitoring are more likely to

[8]The productive contribution of managerial attention in this manufacturing context and the informativeness of these survey measures for managerial attention have been established in previous work (Adhvaryu et al., 2018).

reallocate workers across tasks.

Figure 5

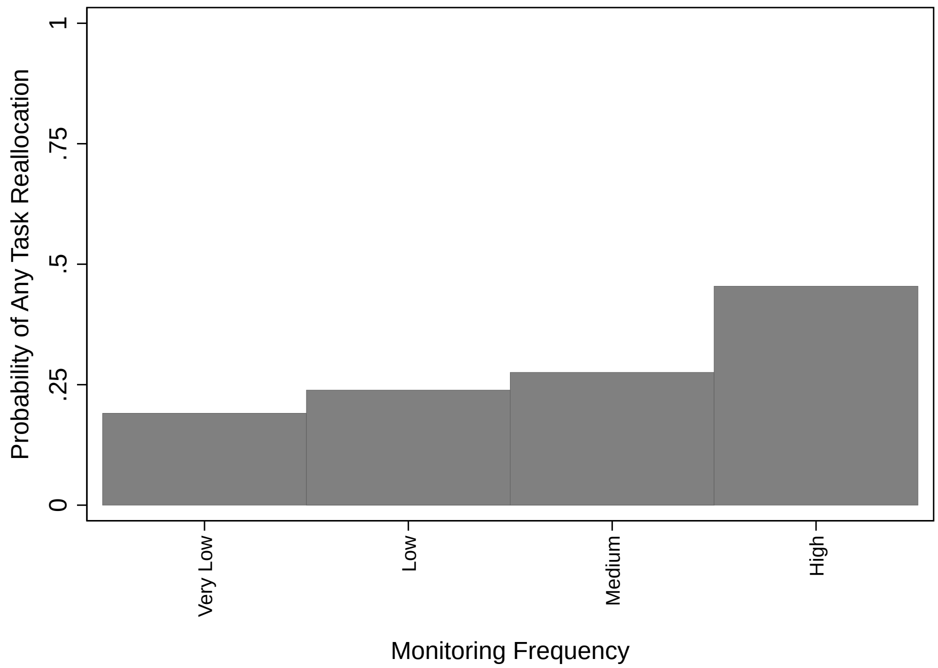


Figure 5 depicts the means of task reallocation across lines and days by the frequency at which the supervisor makes rounds of the lines to monitor for production issues such as bottlenecks. The simple plot of the raw data shows that lines managed by supervisors who monitor production more frequently are more likely to exhibit any reallocation of workers across tasks.

Active Personnel Management Index is constructed from three variables in the survey: 1) a variable recording the number of activities the manager undertakes to resolve issues with under-performing workers; 2) a variable recording the number of activities a manager undertakes to encourage and motivate high performing workers; and 3) a variable recording the number of activities a manager undertakes to retain high performing workers. These variables are normalized and then summed and renormalized to construct a mean effect-style index. This index is then averaged across supervisors of the same line. Higher values of this index denote supervisors who report greater effort (more activities) in addressing these personnel management responsibilities.

We also combine these two indices into a composite factor, which is simply the predicted factor from a factor analysis of these two indices. Accordingly, we interpret higher values of this factor as denoting more attentive managers.[9]

[9] Summary statistics of the two indices and the composite factor are reported in Table A1 of the Appendix.

3.4 Summary Statistics

Table 1 presents summary statistics of the main variables of interest. The mean of fine PM is roughly 51, with a standard deviation of roughly 27. The units of fine PM have been translated as closely as possible to $\mu g/m^3$ in order to conform to the units used in the literature.[10] Table 1 shows that fine PM "shocks" are quite common at both the worker and line level. We define a fine PM "shock" alternately as a fine PM exposure 1 standard deviation above the mean fine PM level for a particular worker at a given hour of day, day of week, and month of year and as a 1 standard deviation increase in fine PM exposure for a given worker from the level that prevailed in the previous hour. Both of these shocks have an incidence of roughly 1 in 4 at the worker-hour level. At the line level, we calculate the proportion of workers on the line experiencing a fine PM exposure that is 1 SD above the mean for that line, hour of day, day of week, and month of year as well as the proportion of workers on the line experiencing a 1 SD rise in fine PM from the previous hour's level. Both of these variables also show that on average 1 in 4 workers on the line are experiencing either shock in a given hour.

Efficiency has a mean of roughly 49, with a standard deviation of 21 at the worker level and 14 at the line level, indicative of the opportunity to mitigate productivity variation at the line level. Task reallocation is quite common, with over 40% of line-hour observations reporting at least one worker reassigned. The mean complexity of operation or task, measured as the number of minutes a hypothetical best operator should take to complete the operation once, is roughly .6, indicating that the mean target quantity per hour across operations is roughly $60/.6 = 100$. The average worker is just under 29 years of age and the mean daily outdoor temperature is roughly 25 degrees Celsius.

4 Empirical Strategy

The empirical analysis proceeds in several steps. We first estimate the degree to which worker productivity is impacted by exposure to fine PM pollution. We do so controlling for contemporaneous coarse PM levels and month, day-of-week, and hour-of-day fixed effects, and show this pattern is robust to various specifications and definitions of the "shock."

We then estimate the degree to which this varies by the specific task (e.g., by task difficulty as measured by SAM) and worker (e.g., by susceptibility as proxied by age). Specifically, we check whether the efficiency losses due to fine PM exposure vary within workers across tasks; that is, we check if

[10] For the sake of comparison, the mean level of fine particulates in Southern CA is 10- 20 $\mu g/m^3$.

Table 1: Summary Statistics

	(1)		(2)	
	Worker-Hour Sample		Line-Hour Sample	
Number of observations	984,740		13,572	
Number of days	213		213	
Number of workers	2126		-	
Number of lines	-		17	
Number of line supervisors	-		24	
	Mean	SD	Mean	SD
Pollution				
Fine PM	50.65	27.51	51.14	27.05
Coarse PM	608.25	242.66	613.66	225.55
1(Fine PM 1SD > Worker-Day-Time Mean)	0.25	0.43		
1(Fine PM 1SD > Worker's Last Hour)	0.23	0.42		
Line Mean [1(Fine PM 1SD > Line-Day-Time Mean)]			0.27	0.41
Line Mean [1(Fine PM 1SD > Worker's Last Hour)]			0.25	0.36
Production				
Hourly Efficiency	49.14	21.11	48.20	14.05
Task Match Adjustment				
Any Task Match Adjustment			0.43	0.50
Other Variables				
Task Complexity (SAM)	0.62	0.20		
Worker Age	28.94	7.69		
Daily Mean Temperature (Celsius)	24.96	2.45		

Notes: The units of fine PM have been translated as closely as possible to micrograms per cubic meter in order to allow for easy comparison with impacts from previous studies. Coarse PM units are raw particle counts per measurement. Efficiency is defined as pieces produced over target pieces.Target is calculated as 60 minutes/standard allowable minute (SAM).

the rank order of most productive task assignments for a given worker changes with exposure to fine PM, presenting an opportunity for managers to mitigate productivity losses by reallocating workers to their most productive assignments under the new ambient conditions. We then check whether at the line level task reallocation indeed responds to pollution shocks. We also estimate to what degree this task reallocation mitigates productivity losses due to pollution exposure at the line level. Finally, we investigate whether lines supervised by more attentive managers exhibit stronger task reallocation responses to pollution shocks and, correspondingly, smaller productivity losses.

4.1 Shocks to Worker Productivity and Heterogeneity

We begin by presenting a non-parametric plot of the gradient of worker efficiency against contemporaneous fine PM exposure, both residualized to net out year, month, day of week, and hour of day fixed effects, as well as coarse PM levels. We then check that the pattern reflected in this plot is preserved in regression analysis, and robust to various specifications and definitions of fine PM "shocks." Specifically, we estimate the following pollution specification for the productivity of worker i at time t, where t varies by hour h, day of the week d, month m and year y:

$$P_{it} = \alpha_0 + \beta FPM_{it} + \phi CPM_{it} + \lambda X_{it} + \psi_y + \eta_m + \delta_d + \gamma_h + \varepsilon_{it} \tag{1}$$

Here, β is the main coefficient of interest, measuring the impact of exposure to fine particulate matter level, FPM, on worker hourly productivity P. Productivity is measured as efficiency (actual pieces produced divided by target quantity) for each worker-hour. We use three alternate definitions of the fine PM shock to demonstrate robustness of the impact of fine PM exposure on productivity. The first is continuous contemporaneous exposure to fine PM in standard deviation units. The second is a binary variable taking value 1 if the current fine PM level to which the worker is exposed is at least 1 standard deviation above the mean level the worker faces at the same hour of day, day of week, month and year, and 0 otherwise. For instance, if the fine PM level to which a particular worker is exposed between 9am and 10am on a given Monday in August 2013 is one SD above the average PM level to which that worker is exposed from 9am to 10am on Mondays on average in August 2013, this variable is 1. The third measure is a binary variable taking value 1 if the current fine PM level to which the worker is exposed is at least 1 standard deviation above the level which the worker faced in the previous hour, and 0 otherwise.

All specifications include some common covariates. ψ_y, η_m, δ_d, and γ_h are year, month, day of week, and hour of day fixed effects, respectively. X_{it} is a vector of additional controls including mean daily temperature, style fixed effects, and, alternately, line or worker fixed effects. Errors are clustered at the date-hour-line-segment level, to account for correlation in the error term at the level of "treatment" (fine PM exposure). We also report errors clustered at the line-date-hour level for robustness. We present robustness results from alternate specifications in the Appendix including, alternately, date, line by date, and line by hour by date fixed effects. We complement this regression evidence with a figure depicting an event study in which we plot residualized efficiency, using this same specification, by hour of the day relative to the hour in which a worker was exposed to a fine PM level 1 SD above the worker-day-time mean.

We then estimate heterogeneity in these pollution impacts on productivity in the following specification:

$$P_{it} = \alpha_0 + \beta FPM_{it} + \beta_Z Z_{it} \times FPM_{it} + \zeta Z_{it} + \phi CPM_{it} + \lambda X_{it} + \psi_y + \eta_m + \delta_d + \gamma_h + \varepsilon_{it} \quad (2)$$

Here Z_{it} is, alternately, a binary for whether complexity (measured as the standard allowable minutes) of the task the worker is doing is above the mean or a binary for whether the worker is of at least median age. We include the same controls from the earlier specification, including coarse PM, daily mean temperature, and time, style and line fixed effects. We focus on the simple continuous contemporaneous measure of fine PM exposure in these regressions. In additional results presented in the Appendix, we show robustness to using the within-worker hour-to-hour shock definition.

Documenting heterogeneity in productivity impacts by task and worker is important for confirming a role for managers to play in mitigating productivity losses (i.e., by reallocating workers across tasks in the presence of productivity shocks). In particular, for task reallocation to be beneficial in mitigating productivity losses due to pollution, it is important that different workers exhibit varying degree of losses due to fine PM exposure on different tasks. If this is the case, then a manager has the opportunity to reallocate a worker who has become particularly unproductive on a given task to a different task on which her productivity is less sensitive to pollution and he can replace her with a worker whose productivity on the original task is less sensitive to pollution.

We investigate whether such an opportunity indeed exists in a series of figures. We first rank operations for each worker according to the mean efficiency the worker achieves during low (first quartile) fine PM exposures in each task (after accounting for time fixed effects and any correlation with coarse PM levels, and ignoring operations for which we observe the worker's productivity for less than half a day). We then compare mean residualized efficiency on each of these operations across low (first quartile) and high (fourth quartile) fine PM levels to see if workers exhibit a pattern of stronger productivity impacts on some of these operations as compared to others. We extend this analysis one step further by splitting the sample according to a measure of the sensitivity of the operation-worker to fine PM exposure. That is, we calculate the variation in productivity across low and high fine PM levels and split the operation-worker observations into above and below median variation.

Finally, we calculate the change in efficiency rank for each operation for each worker moving from low to high PM. Specifically, we investigate whether operations which are higher ranked (i.e., at which the worker is more productive) at low PM levels become lower ranked at high PM levels (i.e., get surpassed in mean productivity by operations which are lower ranked at low PM levels). Similarly, we investigate whether lower ranked operations at low PM levels might actually switch ranks at high PM levels with operations that are higher ranked at low PM levels. If we find this sort of rank-order switching in which operations are most productive for a given worker across PM exposures, it would represent the clearest possible evidence for the role managers can play in mitigating productivity losses.

4.2 Task Reallocation in Response to Pollution

After documenting heterogeneous impacts of pollution on worker productivity and confirming the opportunity for mitigating losses by way of reallocating workers across operations, we investigate the degree to which observed task reallocation responds to pollution shocks. We begin by plotting residualized task reallocation probability at high PM levels across low PM efficiency operation ranks. Here we check whether the operation ranks at which productivity losses appeared largest in the earlier graphs are indeed the same operations from which workers are most likely to be reallocated at higher PM levels (above median).

We then move to a regression analysis of task reallocation at the line level. As workers on a line get exposed to fine PM shocks the manager can either replace that worker, shifting them to an operation for which their productivity is less sensitive to pollution and bring in a worker who is less sensitive to pollution at this operation, or simply add an additional worker to the operation at which the impacted worker is currently assigned. Note then that the worker who is exposed to the pollution shock may or may not be reallocated and the worker who is moved to help the impacted worker may or may not themselves be exposed to a shock. Accordingly, the clearest way to investigate the relationship between task reallocation and pollution is at the line level. That is, if the line on average is exposed to more pollution, or a higher proportion of workers on the line is exposed to shocks, we can expect that the probability of some task reallocation on the line should unequivocally rise.

In fact, the probability of task reallocation should rise as pollution levels deviate from whatever conditions the manager expected to prevail when deciding the original assignment. It could be that managers assign workers under optimal conditions (i.e., lowest PM levels) or perhaps mean levels of PM. We remain agnostic regarding this point, and accordingly present results allowing for the relationship between task reallocation and pollution exposure to be alternately monotonic, symmetric around mean pollution, and piecewise linear with a node at mean pollution levels.

Specifically, we estimate a line-level version of equation 1 with a dummy for any task reallocation this hour on the line as the outcome. We use four different definitions of the fine PM measure: 1) the mean (across workers on the line within hour) continuous contemporaneous fine PM level; 2) the absolute deviation of this measure from the mean fine PM exposure for the line at the same hour of day, day of week, month, and year; 3) a spline in this measure allowing for above and below mean slopes to be asymmetric; and 4) the proportions of workers experiencing a fine PM level 1 SD above and below the mean exposure of the line on the same hour of day, day of week, month and year. We use all of the same controls including time fixed effects, mean daily temperature, coarse PM, style fixed effects and line fixed effects. Standard errors are clustered at the date-hour level. In additional results presented in the Appendix, we show robustness to including date fixed effects as well.

Next, we investigate if the task reallocation response to pollution is sufficient to fully mitigate the impact of pollution on productivity at the line level. We do so by estimating equation 1 at the line level. The three alternate measures for fine PM shocks are defined analogously: 1) mean (across workers on the line within an hour) continuous contemporaneous fine PM levels in standard deviation units, 2) proportion of workers exposed to a level of fine PM 1 SD above the line-day-time mean, 3) the proportion of workers exposed to a level of fine PM 1 SD above the previous hour's exposure. We use mean efficiency across workers in the line in the hour as the outcome and include all the same controls (coarse PM, mean daily temperature, and time, style, and line fixed effects). Once again we show robustness to the inclusion of additional date fixed effects in the Appendix.

4.3 Managerial Attention

Finally, we leverage survey measures of managerial attention to investigate if lines managed by more attentive supervisors exhibit stronger task reallocation responses to pollution shocks, and smaller productivity losses as a result. We do so by estimating equation 2 at the line level for both task reallocation and efficiency as outcomes and using measures of managerial attention as the moderator, Z_{it}. As discussed in section 3, we use three alternate measures of managerial attention. The first captures the frequency at which the manager monitors the line for production issues. The second captures the amount of effort the manager puts forth in personnel matters such as demonstrating tasks to workers and motivating, encouraging, and retaining them. The third measure is a composite of these two obtained from a factor analysis.

When studying efficiency, we simply use mean (across workers on the line within an hour) continuous contemporaneous fine PM levels in standard deviation units. When studying task reallocation, we use, alternately, absolute deviation of mean fine PM across segments within the line from line-day-time mean and a spline in deviations from line-day-time mean PM. We include the same controls as in the previous line level interactions and continue to cluster standard errors at the date-hour level. In the appendix, we report robustness results in which we once again include additional date fixed effects.[11]

5 Results

5.1 Shocks to Worker Productivity and Heterogeneity

We begin by presenting a non-parametric plot of the pollution-productivity gradient. Figure 6 depicts the relationship between residuals of fine PM exposure and efficiency. The plot shows a clear downward sloping gradient, illustrating a loss in worker productivity with increased fine PM exposure. Moving from a low level of fine PM to the highest level reduces efficiency by roughly 3 percentage points or 6% of the mean.

Table 2 presents results from analogous regressions as presented in equation 1. Column 1 reports

[11]We also show results from panel-corrected standard errors (PCSE) models estimated using a feasible GLS estimator, assuming alternately common and panel-specific AR1 disturbances in addition to date-hour level clustering. These estimators are sometimes deemed appropriate when the data set has long T relative to the number of panels (here hour-day observations relative to number of lines). We find the pattern of results to be very similar to our main results.

Figure 6

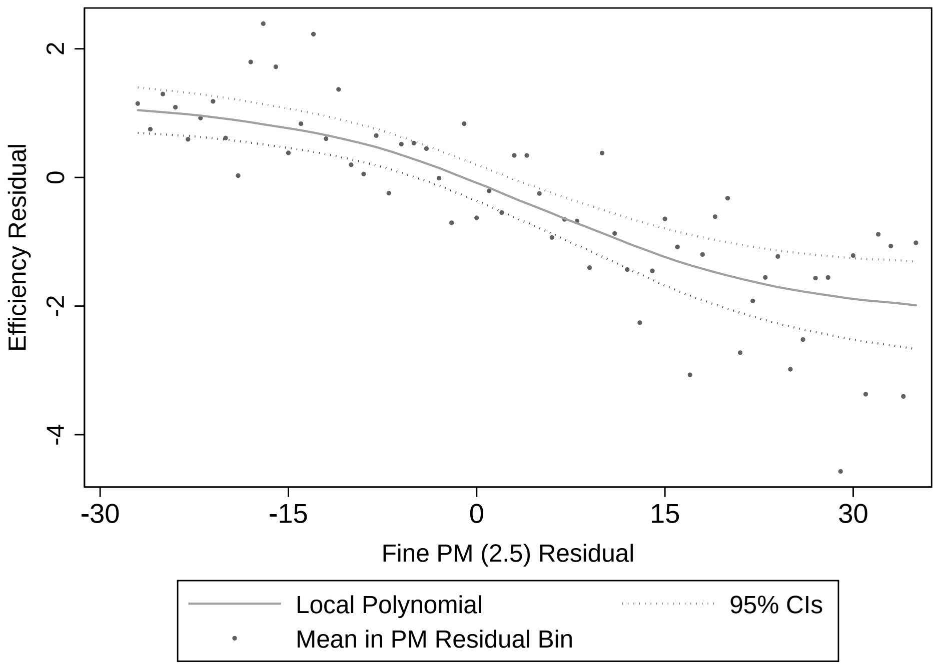


Figure 6 depicts the relationship between residuals of fine PM exposure and efficiency. Residuals are from regressions of each variable on year, month, day of week, and hour of day fixed effects as well as coarse PM. Fine PM residuals are winsorized at the 5th and 95th percentile. Scatter depicts mean residual of efficiency within integer fine PM residual bins. Solid lines depicts local polynomial smooth fit and dotted lines depict 95% confidence intervals.

results from the same specification as that used to produce the residuals plotted in Figure 6 but with the inclusion of line fixed effects, while column 2 replaces line fixed effects with more stringent worker fixed effects. Point estimates indicate that a one SD increase in fine PM reduces worker productivity by roughly 1/3 to 1/2 of a percent. Columns 3 and 4 show that when we focus on large shocks, here a level 1 SD above the mean that worker faces for that day and time, the impact is a bit larger at .6 to .7 percentage points loss in efficiency. The effect persists if we focus only on increases in fine PM of 1 SD hour-to-hour in columns 5 and 6. Additional results presented in Table A2 in the appendix demonstrate robustness to the inclusion of additional date, line by date, and line by hour by date fixed effects, alternately.

We complement these regression results with graphical evidence. Figure 7 depicts an event study of the impact of pollution on worker productivity at the hour level. We first obtain the residual from a regression of efficiency on time fixed effects (year, month, day of week, hour of day) as well as coarse PM and line and style fixed effects. We then calculate the difference in this residual between the hour

Table 2: Pollution and Worker Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Efficiency (pieces produced / target pieces) x 100					
Fine PM (Std)	-0.35359	-0.45876				
	(0.06805)	(0.06699)				
	[0.13836]	[0.14061]				
1(Fine PM 1SD > Worker-Day-Time Mean)			-0.70688	-0.59791		
			(0.11681)	(0.11417)		
			[0.20483]	[0.20658]		
1(Fine PM 1SD > Worker's Last Hour)					-0.53656	-0.33622
					(0.13597)	(0.13411)
					[0.19399]	[0.19524]
Coarse PM Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Line/Worker FE	Line	Worker	Line	Worker	Line	Worker
Observations	984,740	984,740	984,740	984,740	921,805	921,805
Mean of Dependent Variable	49.14					

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at both the date-hour-line segment level (round brackets) to match to monitor-level variation in PM and at the date-hour level (square brackets) allowing for the possibility that PM treatments across the factory are drawn from the same distribution. See Table A2 for robustness to alternate specifications.

of the day in which a worker experienced a fine PM shock (defined as a fine PM level 1 SD above the mean fine PM level that worker is exposed to at that hour and day of week in that month) and each of the 4 hours before and after the shock occurred, focusing on days in which a single such shock occurred for a given worker. We plot the mean of this difference in the efficiency residual for each hour relative to the shock hour along with 95% confidence intervals. Figure 7 shows clear evidence of a sharp onset of a negative impact on productivity at the time of the shock.

We next establish that the impact of pollution on productivity is heterogeneous across workers and operations. We start by estimating equation 2. Column 1 of Table 3 reports estimates of heterogeneity by task complexity and column 2 reports estimates of heterogeneity by worker age. The results indicate that pollution impacts on productivity are roughly 60% larger for workers performing more complex tasks and roughly 35% larger for older workers.[12]

This evidence indicates that when pollution levels rise all workers on all operations will not be impacted the same, suggesting a potential opportunity for reassigning workers to avoid some productivity losses. However, to be sure that such an opportunity exists, impacts should be heterogeneous

[12] In Table A3, we show robustness of estimates from Table 3 to using the within-worker hour-to-hour definition of the fine PM shock.

Figure 7

Figure 7 depicts an event study of the impact of pollution on worker productivity at the hour level. We plot the mean of the difference in the efficiency residual (obtained from a regression on coarse PM and time, line and style fixed effects) for each hour relative to the shock hour along with 95% confidence intervals. For each worker, we focus on the days in which such a shock occurs and we ignore days in which multiple such shocks occur in sequence to make for a clearer illustration.

across operations within workers and workers should differ in their sensitivity to pollution on a particular task, such that there are potential gains from reallocation of workers across tasks. We demonstrate this in a series of figures.

We start by ranking operations for each worker by mean efficiency residuals during first quartile PM times, with the worker having lower mean efficiency on lower ranked operations.[13] In Figure 8, we then plot mean efficiency residual at both first and fourth quartile PM levels for each operation we observe a worker doing in the data, ranked by how efficient the worker is at each operation during low PM times.[14] Figure 8 shows that the loss in efficiency that occurs as PM rises from first quartile levels to fourth quartile levels rises with the efficiency rank of the operation for the worker, such that operations at which the worker averages low efficiency during low PM times do not reflect much impact while

[13]Residuals are obtained from regressions on coarse PM and time, line, and style fixed effects. We keep only the 9 most frequent operations as less than 10% of workers are observed working at more than 10 different operations for more than half a day.

[14]We ignore the least efficient operation for each worker for the sake of this figure and any operation at which we observe the worker for less than half a day.

Table 3: Heterogeneity in Impacts of Pollution on Productivity by Task and Worker

	(1)	(2)
	Efficiency (pieces produced / target pieces) x 100	
Fine PM (Std)	-0.29041	-0.44769
	(0.06843)	(0.07883)
	[0.13407]	[0.14934]
Above Mean Task Complexity X Fine PM (Std)	-0.18964	
	(0.08090)	
	[0.12591]	
Above Mean Task Complexity	7.20897	
	(0.24059)	
	[0.33392]	
Above Median Age X Fine PM (Std)		-0.15988
		(0.05594)
		[0.04414]
Above Median Age		0.57488
		(0.15165)
		[0.12916]
Coarse PM Controls	Yes	Yes
Weather Controls	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes
Style FE	Yes	Yes
Line/Worker FE	Line	Line
Observations	984,740	899,827
Mean of Dependent Variable	49.14	

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at both the date-hour-line segment level (round brackets) to match to monitor-level variation in PM and at the date-hour level (square brackets) allowing for the possibility that PM treatments across the factory are drawn from the same distribution. See Table A3 for results using within worker changes in PM as the exposure measure.

operations at which the worker has higher efficiency potential on average during low PM times are the ones most impacted by PM.

Figure 8

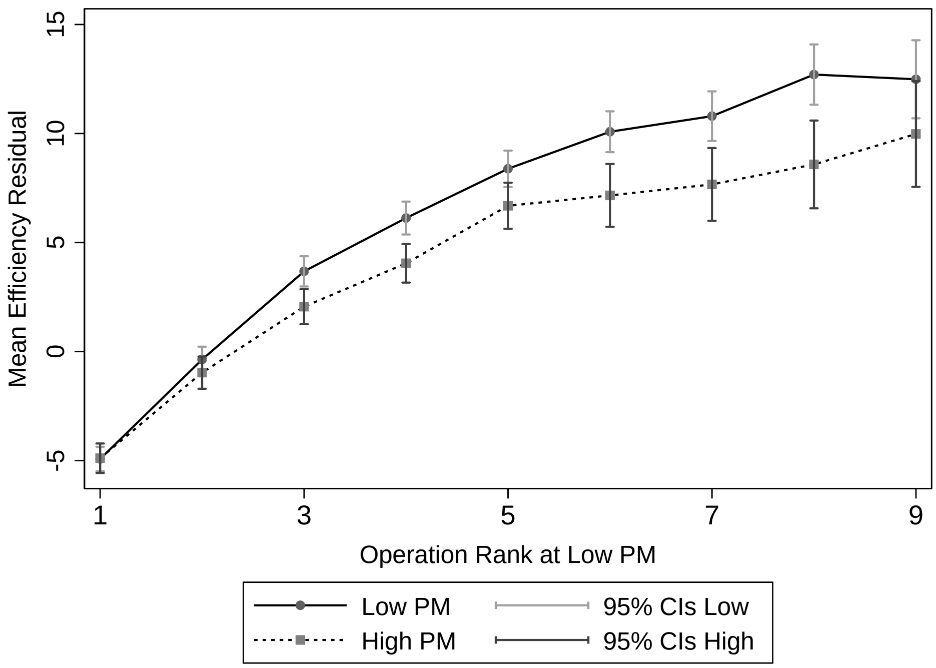


Figure 8 depicts the mean efficiency residual at both first and fourth quartile PM levels for the different operations we observe a worker doing in the data, ranked by how efficient the worker is at each operation during low PM times. The solid line shows, mechanically, that during first quartile PM times mean efficiency is rising in the rank of the operation for the worker. The dashed line shows that at fourth quartile PM times these same workers are significantly less productive at their high ranked operations, but not for their lowest ranked operations.

Next, we split the worker-operation level data into two groups at the median of the standard deviation of efficiency for that worker-operation across fine pm quartiles as a measure of the sensitivity of the worker-operation match to fine PM. We then calculate for each operation rank the points along the two curves depicted in Figure 8, separately for above and below median sensitivity to PM as we defined. We plot the difference between these points at each operation rank for both high and low PM sensitivity subsamples.

Figure 9 shows that the patterns depicted in Figure 8 are heterogeneous across worker-operation matches such that some workers and operations will be more sensitive to PM than others. This illustrates exactly the opportunity the manager faces to forego losses due to PM. That is, the manager can identify workers further to the right on the solid curve and move them along the curve to the left to lower ranked operations for them at which their efficiency will be less impacted and replace them with

Figure 9

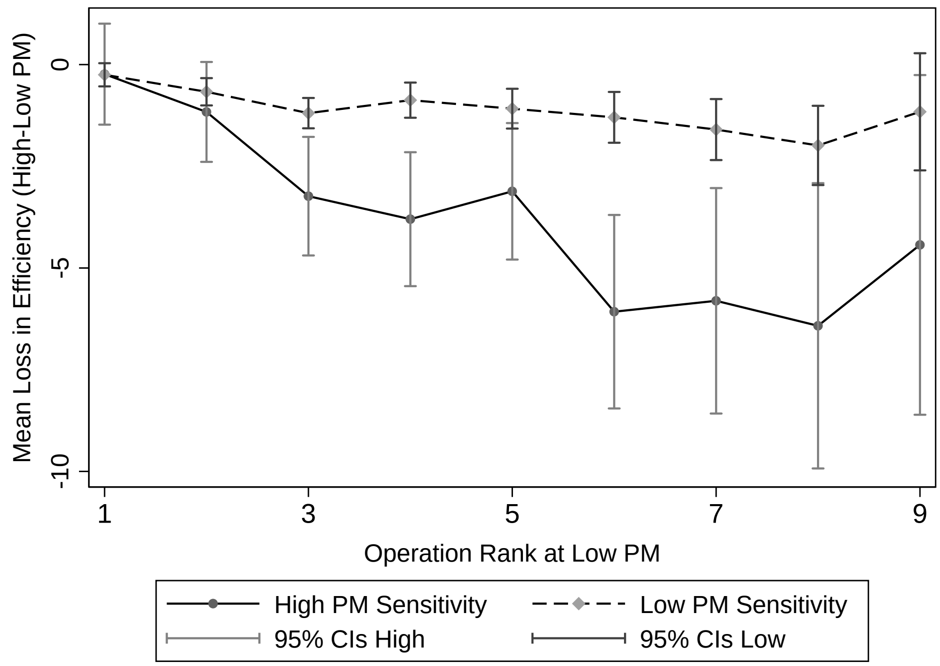


Figure 9 depicts the difference between the two curves in Figure 8 above at each operation rank for two subsamples of the data representing high and low sensitivity to fine PM levels.

workers from the dashed line.

Finally, we check whether for a given worker there is rank-order switching in the efficiency rank of operations as fine PM levels rise. That is, does the most productive assignment for a particular worker change as fine PM levels rise? Figure 10 depicts the within worker change in the efficiency rank of operations across first and fourth quartile PM levels, plotted by operation efficiency rank at first quartile PM levels. We see that lower efficiency rank operations of a worker at low PM levels rise in ranking by nearly 1 spot as PM rises from first quartile levels to fourth quartile levels; while higher efficiency rank operations at low PM levels drop by nearly 2 spots. That is, Figure 10 shows within-worker operation rank-order switching as PM rises. This evidence confirms that as pollution rises, productivity gains can be realized (or productivity losses can be avoided) by reallocating workers across tasks.

Figure 10

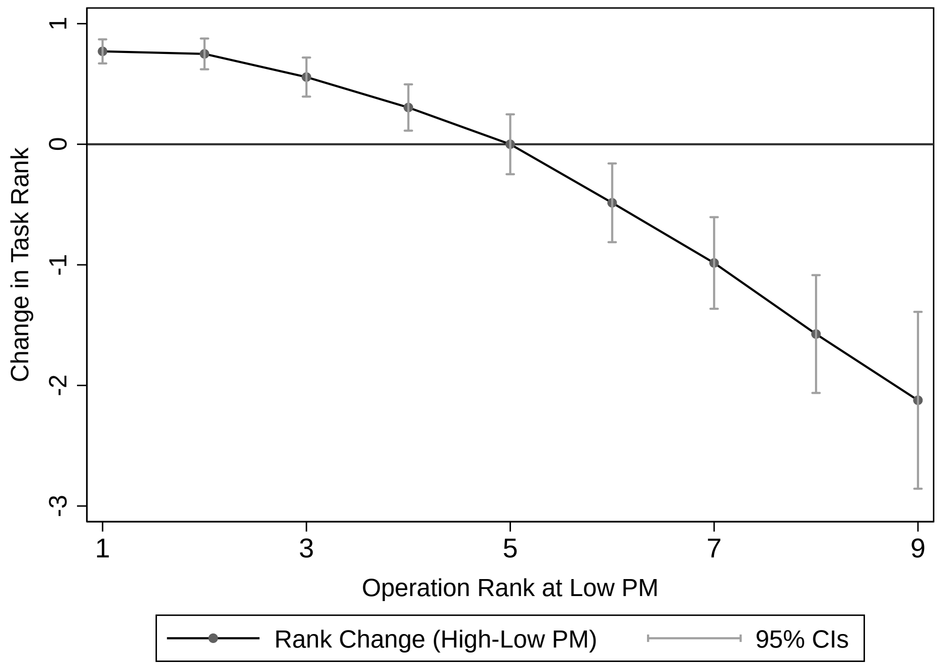


Figure 10 depicts the within worker change in the efficiency rank of operations across first and fourth quartile PM levels, plotted by operation efficiency rank at first quartile PM levels.

5.2 Task Reallocation in Response to Pollution

Having established the opportunity to mitigate productivity losses due to pollution by way of reallocating workers across tasks, we next check that reallocation occurs most often when workers are performing the operations for which we documented efficiency losses being largest. That is, in Figures 8 through 10, we found that the highest efficiency rank operations at low PM levels were the ones at which the potential for efficiency losses were greatest and, accordingly, the opportunity for gains from reallocation were potentially largest. Figure 11 depicts the mean probability that a worker is reallocated when exposed to above median fine PM levels by the efficiency rank of the operation, restricting to lines and days on which at least one such task reallocation occurred. The figure shows that when such reallocation occurs in response to high fine PM levels it is indeed the workers assigned to their higher ranked operations, at which their productivity is more susceptive to losses, who are more likely to be reallocated.

We next present regression results estimating task reallocation responses to fine PM shocks at the line level. Table 4 confirms that task reallocation significantly responds to fine PM exposure. In column

Figure 11

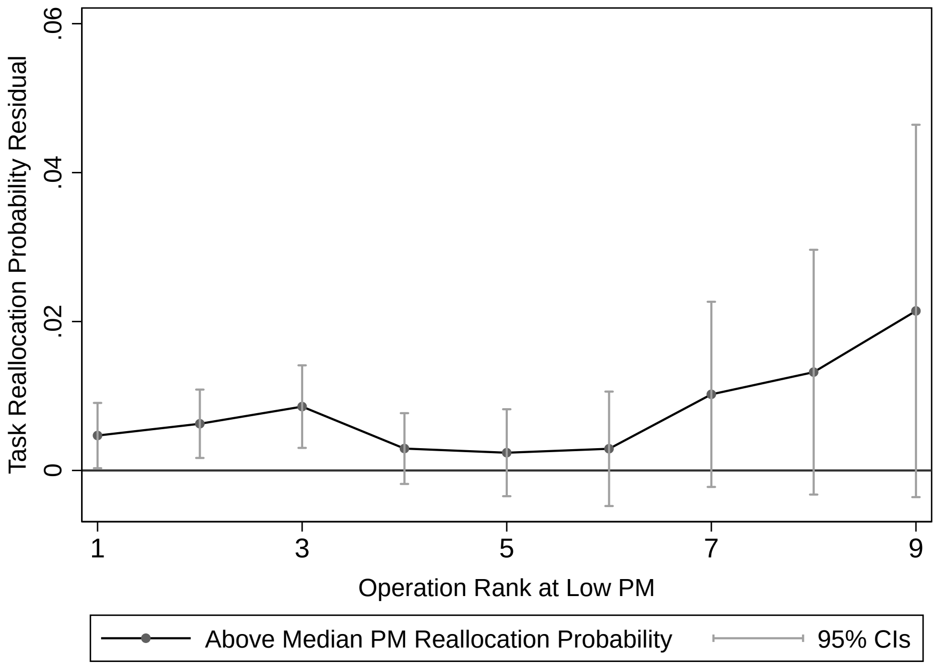


Figure 11 depicts the mean probability that a worker is reallocated when exposed to above median fine PM levels by the efficiency rank of the operation, restricting to lines and days on which at least one such task reallocation occurred.

1, we find that a 1 SD increase in mean fine PM exposure across the line in an hour increases the probability of any task reallocation by nearly 3 percentage points. A similar, though slightly larger estimate obtains in column 2 when we use absolute deviations from the mean. Column 3 shows that all of the task reallocation occurs in response to high levels of fine PM, with no significant response to below mean fine PM realizations. Column 4 shows once again that as the proportion of the line experiencing a positive fine PM shock rises from 0 to 1, the probability of any task reallocation rises by 3 percentage points. We also see that as the proportion of workers experiencing a negative shock on the line rises from 0 to 1, the probability of any task reallocation decreases by nearly 3 percentage points as well.[15]

In Table 5, we show that in similar line-level regression specifications to those in Table 4 that task reallocation responses do not appear to fully mitigate potential productivity losses. That is, we see in column 1 that a one SD increase in the mean fine PM level experienced by workers on the line in an hour reduces productivity by roughly a third of a percentage point. This effect size is similar to

[15] In Table A4, we show robustness of estimates from Table 4 to the inclusion of additional date fixed effects.

Table 4: Pollution and Task Reallocation

	(1)	(2)	(3)	(4)
	Any Task Reallocation 1(at least one worker on line reassigned to a different task this hour from last hour)			
Fine PM (Std)	0.02846			
	(0.00521)			
Absolute Value Deviations from Mean Fine PM		0.03270		
		(0.01001)		
Distance Above Mean Fine PM Spline (Std)			0.04772	
			(0.01109)	
Distance Below Mean Fine PM Spline (Std, Absolute)			-0.00417	
			(0.01386)	
Line Mean [1(Fine PM 1SD > Line-Day-Time Mean)]				0.03098
				(0.01169)
Line Mean [1(Fine PM 1SD < Line-Day-Time Mean)]				-0.02892
				(0.01230)
Coarse PM Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes
Observations	13,295	13,295	13,295	13,295
Mean of Dependent Variable	0.43			

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level. See Table A4 for robustness to alternate specifications.

Table 5: Pollution and Line Productivity

	(1)	(2)	(3)
	Efficiency mean[(pieces produced / target pieces) x 100]		
Fine PM (Std)	-0.34644		
	(0.14439)		
Line Mean [1(Fine PM 1SD > Line-Day-Time Mean)]		-0.38240	
		(0.11325)	
Line Mean [1(Fine PM 1SD > Worker's Last Hour)]			-0.16864
			(0.12149)
Coarse PM Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes
Line FE	Yes	Yes	Yes
Observations	13,295	13,295	12,815
Mean of Dependent Variable		48.09	

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level. See Table A5 for robustness to alternate specifications.

the smallest magnitudes we observed at the worker level; however, columns 2 and 3 clearly indicate smaller effects than at the worker level. If we compare the point estimate from column 2 of Table 5 to columns 3 and 4 of Table 2, we see that a line full of workers experiencing shocks exhibits an average impact of only roughly 1/2 to 2/3 the size of the worker level individual effects. Similarly, comparing column 3 of Table 5 to columns 5 and 6 of Table 2, we see magnitudes 1/3 to 1/2 the size of the worker-level impacts. This pattern of results indicates that managers do in fact mitigate productivity losses to some degree through task reallocation, but are not able to avoid losses altogether.[16]

5.3 Managerial Attention

In these last results, we explore how variation in managerial attention might limit the degree to which some managers are able to utilize task reallocation to fully avoid productivity losses from pollution exposure. In Table 6, we see that more attentive managers (as measured by the composite managerial attention factor) are in fact much more likely to respond to fine PM shocks with any task reallocation. In column 1, we see that a one SD increase in managerial attention more than triples the task reallocation response to fine PM from 3 percentage points to nearly 10 percentage points. Column 2 shows that this additional responsiveness is exhibited for both high and low PM realizations, with more attentive managers responding just as strongly to both high and and low PM realizations and less attentive managers only responding weakly to positive PM realizations. Columns 3 through 6 show that this pattern persists irrespective of whether we measure managerial attention by way of monitoring or personnel management efforts.[17]

Correspondingly, we see in Table 7 that these same attentive managers who respond more to pollution with task reallocation are able to mitigate a large portion of the potential losses to productivity. Columns 1 and 2 show evidence of full mitigation for managers who are one SD above the mean in their attentiveness; while column 3 indicates roughly 25% mitigation when measuring managerial attention using only personnel management efforts. This heterogeneity helps to explain why on average there are still some unmitigated impacts of pollution on productivity at the line level despite the opportunity for task reallocation.[18]

[16]In Table A5, we show robustness of estimates from Table 5 to the inclusion of additional date fixed effects.

[17]In Table A6, we show robustness of estimates from Table 6 to alternative panel-corrected standard errors models estimated by feasible GLS which allow for serially correlated errors in addition to date-hour-level clustering.

[18]In Table A7, we show robustness of estimates from Table 7 to alternative panel-corrected standard errors models estimated by feasible GLS which allow for serially correlated errors in addition to date-hour-level clustering.

Table 6: Pollution and Task Reallocation by Managerial Attention

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Task Reallocation 1(at least one worker on line reassigned to a different task this hour from last hour)					
Absolute Value Deviation from Mean Fine PM	0.03026		0.03150		0.03183	
	(0.01143)		(0.01145)		(0.01145)	
Above Mean Fine PM Spline		0.04776		0.04860		0.04782
		(0.01257)		(0.01267)		(0.01256)
Below Mean Fine PM Spline		-0.00825		-0.00930		-0.00444
		(0.01618)		(0.01610)		(0.01603)
Composite Factor (Std) X Absolute Val Dev Fine PM	0.06873					
	(0.01259)					
Composite Factor (Std) X Above Mean Fine PM Spline		0.04980				
		(0.01451)				
Composite Factor (Std) X Below Mean Fine PM Spline		0.10814				
		(0.01664)				
Monitoring (Std) X Absolute Val Dev Fine PM			0.05224			
			(0.01488)			
Monitoring (Std) X Above Mean PM Spline				0.02251		
				(0.01800)		
Monitoring (Std) X Below Mean PM Spline				0.10908		
				(0.01890)		
Active Personnel Management (Std) X Absolute Val Dev Fine PM					0.05752	
					(0.01132)	
Active Personnel Management (Std) X Above Mean PM Spline						0.04816
						(0.01288)
Active Personnel Management (Std) X Below Mean PM Spline						0.07737
						(0.01496)
Coarse PM Controls and Interactions	Abs Dev	Splines	Abs Dev	Splines	Abs Dev	Splines
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,101	11,101	11,101	11,101	11,101	11,101
Mean of Dependent Variable	0.44					

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level. See Table A6 for robustness to alternate specifications and within-line serial correlation in errors.

Table 7: Pollution and Line Productivity by Managerial Attention

	(1)	(2)	(3)
		Efficiency mean[(pieces produced / target pieces) x 100]	
Fine PM (Std)	-0.50085	-0.46468	-0.51938
	(0.17319)	(0.17352)	(0.17292)
Composite Factor (Std) X Fine PM (Std)	0.49192		
	(0.11245)		
Monitoring (Std) X Fine PM (Std)		0.62149	
		(0.11286)	
Active Personnel Management (Std) X Fine PM (Std)			0.12702
			(0.11189)
Coarse PM Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes
Line FE	Yes	Yes	Yes
Observations	11,101	11,101	11,101
Mean of Dependent Variable		48.46	

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level. See Table A7 for robustness to alternate specifications and within-line serial correlation in errors.

6 Conclusion

How is production organized within firms? How actively do managers intervene in this organization? What actions do high quality managers take to reorganize production in the face of shocks? These questions are core to several disciplines in economics. While much theoretical work shines light on this topic, empirical evidence is limited given the inherent difficulty of observing and recording data inside firms on task allocation, productivity shocks, and team performance.

We seek to fill this gap by leveraging detailed data on hour-by-hour task assignments, productivity shocks induced by sudden changes in exposure to particulate matter pollution, and managerial quality data from a large ready-made garments firm in India. We find that pollution exposure impacts worker productivity, generating heterogeneous impacts based both on worker and task characteristics. We show that this heterogeneity generates returns to reassigning tasks to re-optimize task allocation across production lines. Indeed, we find that managers on average do reallocate tasks during high pollution periods. Moreover, managers shift workers away from tasks for which those workers are idiosyncratically most affected by pollution shocks, as we show there exist other tasks at which these workers suffer less of a decline in productivity from pollution exposure. This implies that managers may often find it optimal to allocate workers to tasks to which they are not particularly well-suited in the absence of shocks. Last, we find that managers who report higher levels of monitoring and effort in personnel management indeed reassign workers to a larger extent during high pollution periods, and those managers also suffer smaller productivity declines as a result of the shocks.

Peering under the hood of firm operations, in the tradition of "insider econometrics," is valuable when it offers the opportunity to learn about the sometimes small day-to-day actions managers take that add up to generate tremendous value for the firm. In this context, we seek to understand what prompts managers to shuffle tasks among workers, and discover how even one or two key changes in task allocation can establish a substantial buffer against the negative impacts of shocks to production line workers.

Learning about which types of managers are able to make these changes is critical to understanding the role of management as a determinant of firm productivity. If managerial inattention is malleable via training (or identifiable via screening), it may be possible to either train managers in this specific regard to equip them better to deal with shocks, or to select better managers on this dimension to achieve the same goal.

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APPENDIX

Not for publication.

A Checks and Robustness

In Table A1, we show expanded summary statistics for the managerial attention indices.

In Table A2, we show robustness of estimates from Table 2 to the inclusion of additional fixed effects, alternately, date, line by date, and line by hour by date.

In Table A3, we show robustness of estimates from Table 3 to using the within-worker hour-to-hour definition of the fine PM shock.

In Table A4, we show robustness of estimates from Table 4 to the inclusion of additional date fixed effects.

In Table A5, we show robustness of estimates from Table 5 to the inclusion of additional date fixed effects.

In Table A6, we show robustness of estimates from Table 6 to alternative panel-corrected standard errors models estimated by feasible GLS which allow for serially correlated errors in addition to date-hour-level clustering.

In Table A7, we show robustness of estimates from Table 7 to alternative panel-corrected standard errors models estimated by feasible GLS which allow for serially correlated errors in addition to date-hour-level clustering.

Table A1: Managerial Attention Indices Summary Statistics

	Frequency	Percent	Standardized Mean Effect Value
Monitoring Index			
Very Low (at most once a day)	21	0.18	-11.02
Low (less than once per hour)	175	1.54	-5.36
Medium (once or twice per hour)	1,141	10.05	-1.59
High (3+ times per hour)	10,020	88.23	0.30
Active Personnel Management Index			
less efforts and activities	1117	9.84	-1.64
|	1109	9.76	-1.26
|	921	8.11	-1.23
|	1141	10.05	-0.57
|	21	0.18	-0.14
motivate/enable underperforming workers,	918	8.08	0.23
encourage/promote high performing workers,	1058	9.32	0.30
retain workers	175	1.54	0.38
|	1078	9.49	0.44
|	683	6.01	0.63
|	996	8.77	0.83
|	1161	10.22	1.07
more efforts and activities	979	8.62	1.48
Composite Factor			
less attentive	21	0.18	-7.60
|	175	1.54	-3.40
|	1,141	10.05	-1.47
|	1,117	9.84	-0.91
|	1,109	9.76	-0.66
|	921	8.11	-0.64
managerial attention	918	8.08	0.36
|	1,058	9.32	0.40
|	1,078	9.49	0.50
|	683	6.01	0.63
|	996	8.77	0.76
|	1,161	10.22	0.93
more attentive	979	8.62	1.21

Notes: Monitoring Index is constructed from a question which asks the frequency at which a manager makes rounds of the lines to check for production issues or imbalances. The response took 7 possible values ranging from less than once a day to every 10 min or more. We first simply normalize this categorical variable to generate an index at the individual supervisor level. There are between 1 and 3 supervisors assigned permanently to each line. These supervisors are not necessarily responsible for subsets of workers or operations, but are collectively responsible for the total line. Accordingly, the responses are then averaged across all supervisors assigned to the line. The resulting variable has 4 possible corresponding to an average across the lines supervisors of rounding at most once a day, less than once per hour, once or twice per hour, more than twice per hour. Active Personnel Management Index is constructed from three variables in the survey: 1) a variable recording the number of activities the manager undertakes to resolve issues with underperforming workers; 2) a variable recording the number of activities a manager undertakes to encourage and motivate high performing workers; and 3) a variable recording the number of activities a manager undertakes to retain high performing workers. These variables are normalized and then summed and renormalized to construct a mean effect style index. This index is then averaged across supervisors of the same line. Higher values of this index denote supervisors who report a greater effort (more activities) in addressing these personnel management responsibilities. The Composite Factor is simply the predicted factor from a factor analysis of these two indices. Higher values of this factor denote more attentive managers.

Table A2: Pollution and Worker Productivity (Robustness to Alternative Specifications)

	(1)	(2)	(3)	(4)	(5)	(6)
			Efficiency (pieces produced / target pieces) x 100			
1(Fine PM 1SD > Worker-Day-Time Mean)	-0.51272	-0.30121	-0.43146			
	(0.12005)	(0.07275)	(0.07549)			
	[0.14601]	[0.09771]	[0.09298]			
1(Fine PM 1SD > Worker's Last Hour)				-0.51314	-0.53659	-0.87477
				(0.13335)	(0.07687)	(0.08364)
				[0.15640]	[0.10321]	(0.10027)
Coarse PM Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional FE	Date	Line x Date	Line x Hour x Date	Date	Line x Date	Line x Hour x Date
Observations	984,740	984,740	984,740	921,805	921,805	921,805
Mean of Dependent Variable			49.14			

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at both the date-hour-line segment level (round brackets) to match to monitor-level variation in PM and at the date-hour level (square brackets) allowing for the possibility that PM treatments across the factory are drawn from the same distribution.

Table A3: Heterogeneous Pollution Impacts by Worker and Task Characteristics (Within Worker-Day PM Shock)

	(1)	(2)
	Efficiency (pieces produced / target pieces) x 100	
1(Fine PM 1SD > Worker's Last Hour)	-0.14695	-0.52475
	(0.13663)	(0.15209)
	[0.19928]	[0.21402]
Above Mean Task Complexity X 1(Fine PM 1SD > Worker's Last Hour)	-1.02912	
	(0.21270)	
	[0.29764]	
Above Mean Task Complexity	7.91562	
	(0.09444)	
	[0.14357]	
Above Median Age X 1(Fine PM 1SD > Worker's Last Hour)		-0.34676
		(0.14159)
		[0.13280]
Above Median Age		0.05083
		(0.06466)
		[0.05465]
Coarse PM Controls	Yes	Yes
Weather Controls	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes
Style FE	Yes	Yes
Line/Worker FE	Line	Line
Observations	921,724	841,950
Mean of Dependent Variable	49.15	

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at both the date-hour-line segment level (round brackets) to match to monitor-level variation in PM and at the date-hour level (square brackets) allowing for the possibility that PM treatments across the factory are drawn from the same distribution.

Table A4: Pollution and Task Reallocation (Robustness to Alternative Specifications)

	(1)	(2)	(3)	(4)
	Any Task Reallocation 1(at least one worker on line reassigned to a different task this hour from last hour)			
Fine PM (Std)	0.00029			
	(0.00609)			
Absolute Value Deviations from Mean Fine PM		0.02221		
		(0.01147)		
Distance Above Mean Fine PM Spline (Std)			0.01498	
			(0.01341)	
Distance Below Mean Fine PM Spline (Std, Absolute)			0.02965	
			(0.01659)	
Line Mean [1(Fine PM 1SD > Line-Day-Time Mean)]				0.02542
				(0.01219)
Line Mean [1(Fine PM 1SD < Line-Day-Time Mean)]				-0.00496
				(0.01370)
Coarse PM Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes
Additional FE	Date	Date	Date	Date
Observations	13,295	13,295	13,295	13,295
Mean of Dependent Variable	0.43			

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level.

Table A5: Pollution and Line Productivity (Robustness to Alternative Specifications)

	(1)	(2)	(3)
	Efficiency mean[(pieces produced / target pieces) x 100]		
Fine PM (Std)	-0.51742		
	(0.12279)		
Line Mean [1(Fine PM 1SD > Line-Day-Time Mean)]		-0.60049	
		(0.10270)	
Line Mean [1(Fine PM 1SD > Worker's Last Hour)]			-0.07040
			(0.10443)
Coarse PM Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes
Line FE	Yes	Yes	Yes
Additional FE	Date	Date	Date
Observations	13,295	13,295	12,815
Mean of Dependent Variable	48.09		

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level.

Table A6: Pollution and Task Match Adjustment by Managerial Attention (Robustness to Alternate Specifications and Estimators)

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Task Reallocation					
	1(at least one worker on line reassigned to a different task this hour from last hour)					
Absolute Value Deviation from Mean Fine PM	0.01937	0.02040	0.02051			
	(0.01400)	(0.01241)	(0.01232)			
Above Mean Fine PM Spline				0.01203	0.01352	0.01294
				(0.01597)	(0.01475)	(0.01468)
Below Mean Fine PM Spline				0.02672	0.02825	0.03032
				(0.02065)	(0.01820)	(0.01805)
Composite Factor (Std) X Absolute Val Dev Fine PM	0.05732	0.05142	0.05068			
	(0.01243)	(0.01145)	(0.01126)			
Composite Factor (Std) X Above Mean Fine PM Spline				0.04058	0.03788	0.03834
				(0.01417)	(0.01288)	(0.01269)
Composite Factor (Std) X Below Mean Fine PM Spline				0.09100	0.07922	0.07573
				(0.01668)	(0.01645)	(0.01619)
Coarse PM Controls and Interactions	Abs Dev	Splines	Abs Dev	Splines	Abs Dev	Splines
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional FE	Date	Date	Date	Date	Date	Date
Estimator	OLS	PCSE (AR1)	PCSE (PSAR1)	OLS	PCSE (AR1)	PCSE (PSAR1)
Observations	11,101	11,101	11,101	11,101	11,101	11,101
Mean of Dependent Variable	0.44					

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level in columns 1 and 4. Columns 2 and 5 present results from a panel corrected standard errors model assuming both contemporaneous correlations in errors at the date-hour level and AR1 errors within the line across time with a common serial correlation parameter across lines. Columns 3 and 6 report results from models similar to those in columns 2 and 5, but with the serial correlation parameter varying across lines.

Table A7: Pollution and Line Productivity by Managerial Attention (Robustness to Alternate Specifications and Estimators)

	(1)	(2)	(3)
		Efficiency mean[(pieces produced / target pieces) x 100]	
Fine PM (Std)	-0.44990	0.13944	0.16124
	(0.14456)	(0.13046)	(0.12900)
Composite Factor (Std) X Fine PM (Std)	0.53083	0.22804	0.21286
	(0.10797)	(0.08564)	(0.08428)
Coarse PM Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes
Line FE	Yes	Yes	Yes
Additional FE	Date	Date	Date
Estimator	OLS	PCSE (AR1)	PCSE (PSAR1)
Observations	11,101	11,101	11,101
Mean of Dependent Variable		48.46	

Notes: Standard errors are reported in brackets below each point estimate. Clustering is done at the date-hour level in column 1. Column 2 presents results from a panel corrected standard errors model assuming both contemporaneous correlations in errors at the date-hour level and AR1 errors within the line across time with a common serial correlation parameter across lines. Column 3 reports results from models similar to those in columns 2 and 5, but with the serial correlation parameter varying across lines.