Management and Shocks to Worker Productivity: Evidence from Air Pollution Exposure in an Indian Garment Factory*

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Abstract

Rapid industrial growth has generated high levels of pollution in many urban areas of developing countries. We study the role of pollution as a tax on worker effort in an Indian garment factory in Bangalore, India. We match hourly, worker-level data on garment production with multiple hourly PM2.5 measurements on two separate production floors and estimate a steep pollution-productivity gradient: a $10\mu g/m^3$ increase in pollution reduces hourly worker efficiency by more than .3 percentage points; a one-standard deviation increase (about 45 $\mu g/m^3$) leads to a 1.4 percentage point (6%) decrease in efficiency. We then document significant heterogeneity in this impact across production lines. We show that capable (i.e., experienced and "relatable") line supervisors are able to flatten this gradient by 25 to 85 percent. Good managers are able to reallocate workers to tasks on high pollution days based on the heterogeneous effects of pollution on worker effort. Thus, in addition to the direct impacts of pollution and other environmental factors, re-optimization of the production process in response to productivity shocks is a mechanism through which management contributes to the productivity gap between firms in developed and developing country settings.

Keywords: worker productivity, pollution, management, ready-made garments, India

JEL Codes: Q53, Q56, M11, M12, O12, O14

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1 Introduction

The process of development inevitably involves the transition of economies from agriculture into manufacturing and other sectors. This is indeed the case for much of the developing world today: labor is shifting steadily from agriculture to industrial employment . Much of this influx of formerly agricultural laborers is into low-skilled manufacturing jobs in urban centers (World Bank, 2012).

While in the long run, the sectoral reallocation of labor away from agriculture may be productivity-enhancing, in the short run, this transition is fraught with frictions. Labor productivity in developing settings lags far behind that of developed country firms, and turnover contributes to already high uncertainty in production capacity and operating costs. Recent studies have shown that labor and total factor productivity is much lower among developing country firms as compared to analogous developed country firms, after accounting for observable inputs and many market frictions, even when focusing on extremely homogeneous technologies and commoditized goods (see, e.g., Bloom et al. (2012) for a review of this evidence).

Noting that many of the world's largest garment exporting countries (e.g. India, Bangladesh, China, Turkey) also have the world's highest recorded levels of fine particulate matter, this paper provides strong empirical evidence of the degree to which adverse environmental conditions impact labor productivity and of the role of management in potential mitigation of these impacts.[1]

Using detailed, high-frequency data on hourly, worker-level garment production and multiple, hourly measurements of both fine and coarse particulate matter levels across two productions floors in a garment factory in Bangalore, India, we estimate a steep pollution-productivity gradient. We find that an increase in fine PM levels of roughly 10 micrograms per cubic meter leads to a reduction in hourly worker efficiency of roughly .3 percentage points; a one SD increase in fine PM levels (roughly 45 micrograms per cubic meter) leads to a large 1.4 percentage point decrease in hourly worker efficiency.

Perhaps most interesting is the smaller impact observed on lines managed by more experienced and more relatable supervisors (i.e., younger, less educated, and with the same native language and hometown as their workers). We interpret this heterogeneity as strong evidence of a role for management in impact mitigation. Indeed, we find that more experienced and relatable supervisors are 3-4% more likely to reallocate the workers on their lines across tasks in response to a rise in pollution than

[1] See, e.g., Krzyzanowski et al. (2014) for a list of cities of the world with the highest fine particulates levels.

their less experienced and less relatable counterparts, resulting in up to 85% mitigation of the impact of fine PM on worker hour efficiency.

This paper contributes to three distinct literatures. First, we provide rigorous estimates of a negative gradient between air pollution and worker productivity using a wealth of micro data with unique granularity and frequency from a developing country setting with high pollution levels. Recent studies have documented impacts of temperature on agricultural and industrial productivity and labor supplies in both developed and developing country settings, as well as impacts of exposure to air pollution on worker productivity in the US (Adhvaryu et al., 2014; Chang et al., 2014; Dell et al., 2012; Graff Zivin and Neidell, 2010, 2012). We add to this literature estimates of the impacts of high levels of air pollution on worker productivity in labor-intensive manufacturing in a developing country setting with roughly 4 times the levels of fine particulates in the US on average. Our estimates are particularly relevant and informative for policy and research in that the vast majority of the world's labor-intensive manufacturing is done in developing country settings with extremely high levels of air pollution and this specialization will only continue to intensify in the coming years.

Furthermore, the richness of our data permits us to comment on the heterogeneity of these impacts by worker and task. We are accordingly able to contribute to a second growing literature on the existence and determinants of the gap in labor and total factor productivity across developed and developing country settings. Early studies documented a large degree of residual variation in labor and total factor productivity across large and small firms within countries as well as in mean or even tail productivities across developed and developing countries, even in extremely homogeneous and commoditized industries. Recent studies have provided evidence that labor regulation, financial market frictions, limited competition and resulting technological innovation, ethnic and cultural frictions, infrastructural failures, and differences in organizational behavior might all contribute to these discrepancies (Allcott et al., 2014; Bloom et al., 2010a; Bloom and Van Reenen, 2010; Hjort, 2013; Tybout, 2000). We add to this list of determinants adverse work environments. In this respect, the results in this paper strongly complement our earlier work documenting the existence of a markedly negative temperature-productivity gradient (Adhvaryu et al., 2014).

Lastly, we contribute to a newer, rapidly growing strand of literature modeling and measuring the role of management and organizational behavior in determining worker productivity and resilience to shocks, particularly as these elements differ across developed and developing country firms (Bloom et al., 2013; Bloom and Reenen, 2011; Bloom et al., 2010b,b; Bloom and Van Reenen, 2007, 2010; Bruhn et al., 2010; Lazear et al., 2014; Schoar, 2014). We show that supervisor experience and the worker-management match produce a great deal of heterogeneity in the pollution-productivity gradient. Furthermore, we document that dynamic worker-task match adjustments are at least one specific way in which supervisor can actively augment impacts of adverse working conditions. In this way, re-optimization, or lack thereof, in response to productivity shocks (whether deriving from pollution, power outages, infrastructural failures, or other frictions frequently faced in developing countries) is one important mechanism by which management contributes to the productivity gap between developed and developing country firms (as shown proposed in recent studies), in addition to the direct contributions of frequent productivity shocks themselves.

The rest of the paper is organized as follows. Section 2 discusses the garment industry and the specific garment production process in the study factory. Section 4 discusses our data sources. Section 5 describes our empirical strategy. Section 6 describes the results. Section 7 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 maximizing productivity, and the physiology underlying the impacts of pollution on worker productivity.

2.1 The Indian Garment 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. With the steady transition of the employment share in India, and in much of the developing world, from rural agricultural self-employment to urban and peri-urban wage labor, the garment sector represents an unparalleled capacity to absorb this current and future influx of young, unskilled and semi-skilled labor (World Bank, 2012). Furthermore, women comprise the majority of the global garment workforce; and new labor force entrants tend to be disproportionately female in contexts like India where the baseline female labor force participation rate is low (Staritz, 2010). The partner firm in this research is the largest private garment exporter in India, and the single largest employer of unskilled and semi-skilled female labor in the country.

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 3 reasons. First, sewing makes up roughly 80% of the factory's total labor employment; and is, therefore, the most appropriate setting to study the impacts of shocks to worker productivity. Second, output is measurable for each worker for each hour on the sewing floor and is particularly comparable across workers, lines, and garments being produced. Third, the number of lines, and hence supervisors, is sufficiently large and the mapping of workers to supervisors is sufficiently dynamic, yet clearly observable to allow for the study of the interaction between supervisors and workers experiencing shocks to productivity.

On the sewing floors of the factory we study in this paper, garments are sewn in production lines consisting of 50-150 workers (depending on the complexity of the style) arranged in sequence and grouped in terms of segments of the garment (e.g. sleeve, collar, placket). Roughly 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 will produce 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 order for that garment is met).[2] 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.

Before reaching the sewing floor, pieces of fabric needed for each segment of the garment are cut using patterns from a single sheet so as to perfectly match on color and fabric quality. These pieces are divided according to groups of sewing operations (e.g. sleeve construction, collar attachment) and pieces for 10-20 garments are grouped and tied into bundles. These bundles are then transported to the sewing floors where they are distributed across the line at various "feeding points" for each group of sewing operations.

In finishing, garments are checked, ironed, and packed. A great degree of quality checking is done "in-line" on the sewing floor, but final checking occurs in the finishing stage. Any garments with quality issues are sent back to the sewing floor for rework or, if irreparably ruined, are discarded before

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

packing. Orders are then packed and sent to port.

2.2.1 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 at the beginning of each day to optimize the garment-specific productivity subject to the manpower constraints that day. Accordingly, on any given day, between 10 and 50% of workers will be assigned to lines other than their usual production lines.

In addition to the worker composition of the line, the supervisor must also assign 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. Then, during the production day, one of the main responsibilities of the supervisor is to dynamically adjust this initial worker-task match to continually optimize performance based on observed, realized performance in previous hours. These adjustments, termed "line-balancing," might involve switching two workers across two tasks, or even doubling up the number of workers on a particular operation in order to move a more efficient worker to a particularly complex task. Given the complex interrelationships between the productivity of different 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 the supervisor and the factory), "line-balancing" is perhaps the most important mechanism by which factory management can respond to worker-specific productivity shocks; and is, therefore, an important determinant of marginal productivity on the sewing floor.

2.3 Physiology of the Pollution-Productivity Gradient

A vast literature 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 particulates (greater than 2.5 micrometers (μm)), fine particulate matter (less than or equal to 2.5 μm), and ultra-fine particles (<0.1 μm). The focus on this study in on the second category, fine particulate matter. Fine PM has been shown to have the largest health impacts of the three, for a variety of factors - 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 chemical composition that is more harmful and penetrate indoor environments more easily (Pope and Dockery, 2006).

Long-term exposures have been linked to a variety of health 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. However, short-term exposures, such as those in experimental laboratory settings have also found elevated health risks. For instance, studies that have exposed healthy human subjects to fine PM for short periods (in concentrations currently found in cities) in the laboratory find evidence of adverse cardiovascular effects (Mills et al., 2005), as well as acute constriction of the blood vessels, which may also increase the probability of cardiac events (Brook et al., 2002). Thus, short-term exposure to fine PM may potentially impair functioning of otherwise healthy adults, and long-term exposure is linked to severe health and mortality risks.

3 Model

We develop a simple model of worker effort and task allocation to illustrate the mechanism through which pollution affects productivity, and the way in which supervisors ameliorate the negative impact of pollution on productivity.

3.1 Worker effort

Consider a line made up of N workers, indexed by i managed by a supervisor indexed s. Each worker chooses a level of effort e to put forth subject to a cost of effort function c and utility or monetary benefit function b. We introduce individual worker-specific heterogeneity in cost of effort through a scalar multiplier α_i.

Pollution is represented as a (normalized) effort cost, $\delta_t \sim \mathcal{N}(0, \sigma^2)$, varying across time t and common to all workers, but substitutable with effort with individual-specific substitution factor γ_i. Pollution is observed (or perhaps "felt" is a better word) by the worker, but not by the supervisor. Moreover,it is felt differentially by each worker (as indicated by substitution factor γ_i), generating heterogeneity in the impacts on optimal effort for each worker.

Worker i chooses optimal effort level e^*_{it} as follows:

$$e^*_{it} = \arg\max_{e \in \mathbb{R}} \; be - \alpha_i c(e + \gamma_i \delta_t). \tag{1}$$

Then, the necessary first order condition is:

$$\frac{b}{\alpha_i} = c_e(e + \gamma_i \delta_t). \tag{2}$$

Since c_e is invertible, we can define c_e^{-1} and thus get optimal effort e^*_{it} as

$$e^*_{it} \quad = \quad \underbrace{c_e^{-1}\left(\frac{b}{\alpha_i}\right)}_{\text{Observed by worker and sup}} \quad - \quad \underbrace{\gamma_i \delta_t}_{\text{Unobserved by sup}} \tag{3}$$

where the second term is unobserved by supervisors, as indicated. Optimal effort is thus an increasing function of the monetary return to effort; and a decreasing function of the individual-specific scalar modifier on effort cost, and the individual-specific effort cost of pollution, $\gamma_i \delta_t$.

3.2 Production and the Role of Supervisors

Next, we map worker-level effort and production to line production and introduce the role of the supervisors in production. A line produces quantity q_t of a garment at time t through the completion of N tasks, indexed by j. Supervisor s attached to a given line will allocate workers to tasks within the line each hour. The production from each task in each period t is given by $q_{jt} = k_j e_t$. The line production is then the sum of each task's production, so that

$$q_t = \sum_{j=1}^{N} q_{jt} = \sum_{j=1}^{N} k_j e^j_t \tag{4}$$

where e^j_t denotes effort expended on task j at time t. Given the linear production function, the optimal allocation will be to assign the worker with the highest (expected) effort to the task with the highest return to effort, i.e., with the maximum k_j; the next highest effort to the task with the second highest return, and so on.

Assignment of workers to tasks is done through the ordering function $o : \{1, 2, ..., N\} \mapsto \{1, 2, ..., N\}$.

o takes workers $i \in \{1, 2, ..., N\}$ and maps them to tasks $j \in \{1, 2, ..., N\}$. Define the set of all possible such mappings as Ω, and elements of this set as $o \in \Omega$. For each level of pollution δ, there exists an optimal mapping o^*_δ, which satisfies $o^*_\delta = \arg\max_{o \in \Omega} \; q^o_\delta$, where q^o_δ is the line production under task mapping o at pollution level δ. Note that δ factors linearly into workers' optimal effort choices, but that given the heterogeneous coefficients on the pollution cost (γ_i), shifts in δ can change the rank ordering of workers' effort choices. (Indeed, for shifts in pollution to change optimal allocation patterns, it must be the case that the rank ordering of optimal effort levels changes at least once.)

Supervisor s observes output (and can thus calculate how much effort was expended by each worker), at the end of each period. However, the supervisor cannot necessarily perfectly predict workers' efforts on specific tasks *before* allocating workers to tasks unless he allocates effort to observe production as it is ongoing.

Specifically, if a supervisor invests his own effort (at a supervisor-specific cost of effort, λ_s) in monitoring workers during production, then he is able to predict perfectly a worker's effort before allocation is done. If supervisor s invest effort in monitoring ($I = 1$) in a given period t, then the supervisor chooses the allocation that maximizes total output, given by equation 4. When $I = 1$, the optimal effort of each worker is observed fully (including the effort costs of pollution felt by each worker), and thus allocation can be done optimally, such that the highest (realized) effort in period t is paired with the task that has highest productive return on effort. Thus in each period when $I = 1$, maximal production given δ pollution, $q^{o^*}_\delta$, is obtained.

On the other hand, if the supervisor chooses not to invest effort in monitoring, such that $I = 0$, then he maximizes expected output by allocating workers to tasks based on the *expectation* of their effort. Expected optimal effort for each worker from the supervisor's perspective is:

$$\mathbb{E}\; e^*_{it} = c_e^{-1}\left(\frac{b}{\alpha_i}\right) - \mathbb{E}\;\gamma_i\delta_t = c_e^{-1}\left(\frac{b}{\alpha_i}\right), \tag{5}$$

which is fixed across t, since $\mathbb{E}\;\gamma_i\delta_t = 0$ for all t.

Since we have made the simplifying assumption that production is linear in effort, expected production for a given task-worker match will simply be $k_j \mathbb{E}\; e^j_t$, and so for a given allocation $o \in \Omega$, expected output is:

$$\mathbb{E}\ q^o = \sum_{j=1}^{N} k_j \mathbb{E}\ e_o^j. \tag{6}$$

The supervisor who chooses not to invest in observing effort ($I = 0$) thus picks the task mapping that generates the maximum expected production. That is, the supervisor chooses

$$o'^* = \arg\max_{o \in \Omega} \mathbb{E}\ q^o. \tag{7}$$

The supervisor's problem in each period is therefore to choose whether or not to invest in observing worker-specific effort before task allocation is done. We assume supervisors wish to maximize expected production. The supervisor evaluates the predicted gains from observing effort before task allocation against the cost (λ_s) associated with investing in effort. He evaluates this potential gain over the distribution of γ. That is, for given γ, if he chooses $I = 1$, he will be able to allocate optimally according to the actual optimal effort contributions of each worker, and thus realized production will be $q_\delta^{o^*}$. For all γ, if he chooses not to invest ($I = 0$), realized production will $q^{o'^*}$. Thus his decision is to choose $I = 1$ if and only if

$$\lambda_s < \int_{\delta \in \mathbb{R}} q_\delta^{o^*} f(\delta) d\delta - q^{o'^*}, \tag{8}$$

where $f(\delta)$ is the probability density function for $\mathcal{N}(0, \sigma^2)$, the distribution from which δ is drawn. The above inequality captures the intuitive idea that if the supervisor chooses to invest if his cost of effort is small relative to the predicted gains from investing in observing his workers closely.

Note that this inequality does not vary by t, and thus the right-hand side quantity $\int_{\delta \in \mathbb{R}} q_\delta^{o^*} f(\delta) d\delta - q^{o'^*}$ defines a cutoff in the distribution of λ_s, such that all supervisors with λ_s smaller than this cutoff will always choose to invest in observing their workers closely, while those with λ_s above the cutoff will never invest and will thus never shift the task mapping from the optimum for the expected effort levels of their workers.

It is straightforward to extend the model such that supervisor cost of effort varies stochastically from day to day. In this extension, supervisors are differentiated by the fact that they draw their λ_t from distributions with different means. It is then simple to show that the *probability* that a "high type" supervisor (one with a smaller distribution mean) invests will be higher than the *probability* a low type invests.

3.3 Implications

To summarize, the framework laid out above provides some intuitive predictions regarding the impacts of pollution on worker and line productivity, and the role of supervisors in mitigating the impacts of pollution.

- First, by assumption, worker and line productivity are negatively affected by pollution.
- Second, at any given level of pollution, supervisors that invest effort in monitoring will achieve higher production on their lines, on average, than those who do not invest effort in monitoring.
- Third, supervisors with low-enough costs of monitoring effort λ_s will invest in monitoring each period. If the rank ordering of optimal effort changes with pollution, then these supervisors will reallocate workers to tasks in response to changes in pollution across periods. As a result, "high-type" supervisors will achieve optimal production on their line at all levels of pollution.
- Fourth, larger deviations in pollution levels will generate greater probability of task shuffling, because rank order switching is more likely with large δ shocks.

In our empirical analysis, we test these predictions using data on pollution, worker-level productivity, supervisor characteristics, and worker-task reallocations. We consider supervisors that are more experienced and more similar or relatable to their workers as those with lower costs of monitoring effort λ_s.

4 Data

4.1 Pollution Data

The air pollution data used in this study were collected using 5 particulate matter monitors positioned at different locations across the 2 sewing floors of the garment factory.[3] Two monitors were placed on the first floor on which lines 1 through 9, along with an occasional line 10, are located; and the remaining three monitors were placed on the second floor on which lines 11 through 17 are located.

[3] The monitors used were custom calibrated particulate matter count monitors.

The monitors were calibrated to collect two distinct counts of particulates: 1) those equal to or smaller than 2.5 microns in diameter, denoted here as fine particulates, and 2) those between 2.5 and 10 microns in diameter, denoted here as coarse particulates. In the analysis that follows, we focus on the impacts of fine particulate matter (PM) on efficiency controlling for coarse PM. We do so because fine PM is extremely 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 produced by the garment production process and could therefore exhibit a reverse causality relationship; i.e., high efficiency produces high coarse PM levels. Lastly, the environmental and medical literatures suggest that fine PM is the more impactful of the two particulates due to its ability to accumulate in the lungs and restrict respiration.

4.1.1 Fine Particulates (PM 2.5)

We can check the exogeneity of fine PM levels 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 which we hypothesize is endogenous to production. We can also check the robustness of our results to instrumenting for contemporaneous fine PM levels using future fine PM levels from the same day and controlling for the day's average fine PM level. Results of these checks are presented in the figures and tables in the appendix. Lastly, it is clear that to the degree that fine PM is in fact produced by the manufacturing process, this reverse causality will bias estimates of the *negative* impact of fine PM exposure on worker productivity towards zero.

Figure 1A

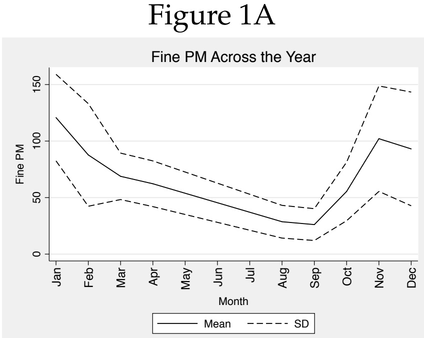


Figure 1B

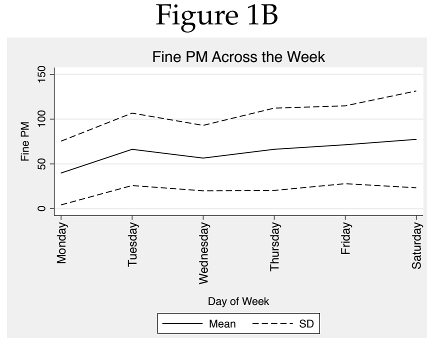
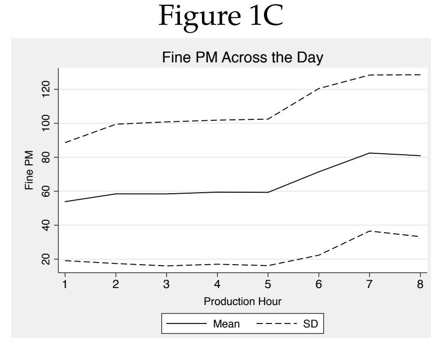


Figure 1C



As shown in Figures 1A-1C, fine PM levels vary systematically by month or season of the year, as well as day of week and hour of the day. Specifically, fine PM levels tend to be highest on average in the winter months, later in the week, and at the end of the production day. These patterns likely reflect the burning of carbon-based fuels for heating and industrial energy demand as well as automobile traffic patterns. Note that the PM data used in this study are available from August 2013 through April 2014.

4.2 Production Data

The production data used in this study is collected using tablet computers assigned to each production line on the sewing floor. Each production writer, traditionally charged with recording by hand on paper each machine operator's completed operations each hour for the line, was trained to input production data directly in the tablet computer. Whereas traditionally this operator-hour level data would be tallied by hand and the sum for the entire line at the end of each hour, or even often the day, would be digitally entered into the production database, with the introduction of the tablet computers no manual tabulation or entry was necessary. In this way, we were able to preserve the most granular, disaggregated, and accurate data at the worker by hour level.

4.2.1 Efficiency

The key measure of worker productivity we study below is *efficiency*. This measure is calculated as actual quantity produced divided by the target quantity per unit time, here hour. The target quantity for a given garment is calculated using a measure of garment complexity called the *standard allowable minute* (SAM). The SAM is defined as the number of minutes that should be required for a single garment of a particular style to be produced. That is, a garment style with a SAM of .5 is deemed to take a half minute to produce one complete garment. The SAM, as the name denotes, is standardized across the global garment industry and is drawn from an industrial engineering database. The SAM, however, might be amended to account for stylistic variations from the representative garment style in the database. Any amendments are explored and suggested by the sampling department in which master tailors make samples for costing purposes of each specific style to be produced in the near future by lines on the sewing floor.

The target quantity for a given unit of time for 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 line in an hour for a style with a SAM of .5 will be $60/.5 = 120$. Then, the target quantity for a given worker completing a particular operation in the production of this same garment will be the target quantity for the hour for the line multiplied by the number of times the specific operation for which the worker is responsible has to be completed to produce a single garment. That is, if a worker is for example sewing the sleeves on the body of the shirt, the worker must complete the operation 2 times in order for a single shirt to be produced; and thus, her target quantity for an hour of producing this same garment with a SAM of .5 is 2 x 120 = 240. Then, recall that if this worker completes only 180 sleeve to body attachments in a given hour, her actual efficiency will be $180/240 = 75\%$. In this way, efficiency is the most comparable measure of productivity across garments being produced by different lines at a given time and even of productivity across workers completing different operations on the same line producing the same garment at a given time. That is, efficiency is appropriately standardized by garment and task complexity.

Figure 1D

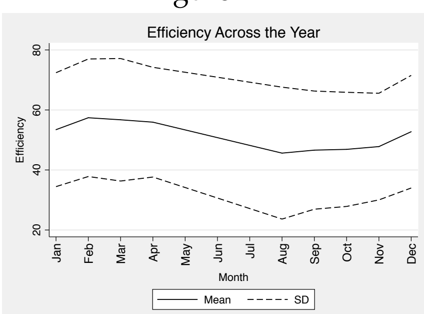


Figure 1E

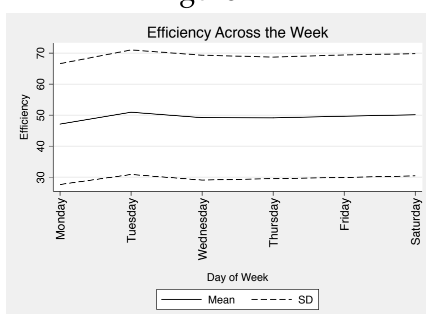
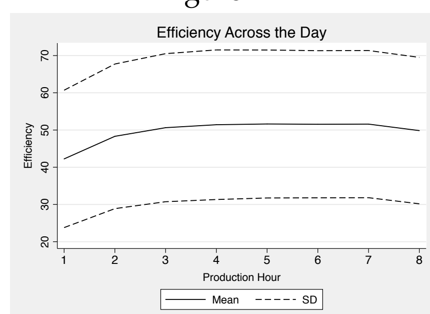


Figure 1F



As shown in Figures 1D-1F, worker efficiency also follows mild seasonal, day of week, hour of day patterns. Specifically, efficiency peaks around March with late winter and early spring showing high mean efficiency as well. Also, Mondays tend to lag behind the rest of the days of the week in efficiency, and the efficiency trends upwards through the first 2-3 hours of the day before plateauing through the rest of the work day.

These patterns are somewhat coincident with the patterns in fine PM and might convolute the analysis of causal impacts of fine PM on efficiency and other work outcomes. Accordingly, we will restrict our attention in the ensuing analysis to comparisons within month, day of week, and hour of the day.

4.3 Human Resources Data

Data on personal details of workers and the line supervisors are kept in a firm-managed database. These data linked to worker ID numbers were shared with us. The variables available in this data include date of birth, date on which the worker joined the firm, gender, native language, home town, and education. We use these data to explore heterogeneity among workers in impacts as well as heterogeneity by supervisor experience and similarity to the workers.

4.4 Attendance and Health Clinic Data

Data on individual worker attendance, as well as time clocking in and out, is collected by the factory using biometric scanning devices. This data is stored in a central human resources database and indexed by worker ID number and date. We use attendance to data to check that selective attendance and workforce composition are not convoluting our main analysis.

A health clinic is maintained on the factory grounds. All employees are free to utilize the services and products offered at the clinic. A full-time nurse attends the clinic and is sometimes joined by a physician who rotates between several of the factory units run by the same firm. The worker ID numbers, symptoms, diagnoses, and treatments are recorded for each of the patient visits each day. We match this data by worker ID numbers to hourly productivity data and particulate matter exposure on the production floor. We use health clinic data to check for impacts of fine PM exposure on quantity of time spent producing as a check of the proposed mechanism of impact (i.e., pollution impacts intensive margin effort and efficiency of workers).

4.5 Summary Statistics

Table 1 presents summary statistics of the main variables of interest in the data. Note that the mean level of fine PM in our whole sample is roughly 65 with a standard deviation of nearly 45. 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 in other contexts.[4] Columns 2 and 3 show observation counts, means and standard deviations for the above and below median fine PM level sub-samples. The top panel shows that all lines and nearly all workers are observed during exposure to both high and low fine PM levels. Also, the number of days and worker-hour observations are

[4]For the sake of comparison, the mean level of fine particulates in Southern CA is between 10 and 20 micrograms per cubic meter.

roughly balanced across high and low PM sub-samples. Lastly, both hourly efficiency and coarse PM levels are higher on average in the low fine PM sub-sample than in the high fine PM sub-sample, consistent with a negative impact of fine PM on efficiency and a positive association between coarse PM and efficiency due to reverse causality.

5 Empirical Strategy

5.1 Overview of strategy

The empirical analysis undertaken in this study proceeds in several parts. We first estimate the contemporaneous efficiency-fine-PM gradient, controlling for contemporaneous coarse PM levels and month, day-of-week, and hour-of-day fixed effects. We also establish robustness of these estimates to alternative specifications including worker and/or line fixed effects. We also estimate non-linearity in the gradient by quartiles of the fine PM distribution, estimating the slope within each quartile separately.

The next phase of the analysis documents heterogeneity in the slope of this gradient across production lines and explores the degree to which supervisor characteristics (i.e., experience and relatability in terms of age, education, and language) can explain these differential slopes. Again, we estimate differences in linear slopes as well as contributions of supervisor characteristics to non-linearities by quartile of the fine PM distribution.

Lastly, we explore more specifically *how* supervisors might be able to avoid or offset large losses due to high particulate matter exposure. That is, we estimate the relationship between fine PM levels and adjustments in worker-task matches in response to resulting efficiency losses. In order to complement estimates from nonlinearities in the pollution-efficiency gradient, we also estimate quartile specific impacts of fine PM on worker-task adjustments.

5.2 Specifications

We estimate the following base specification, for the efficiency of worker i in hour h on day of the week d in month m:

$$E_{ihdm} = \alpha_0 + \beta FPM_{fhdm} + \phi CPM_{fhdm} + \gamma_h + \eta_m + \delta_d + \varepsilon_{ihdm} \quad (9)$$

Here, β is the main coefficients of interest, measuring the impact of exposure to fine particulate

Table 1
Summary Statistics

	(1)		(2)		(5)	
	Whole Sample		***Low PM***		***High PM***	
Number of worker-hour observations	860,804		430,790		430,014	
Number of lines	17		17		17	
Number of workers	1763		1755		1738	
Number of days	178		119		133	
	Mean	SD	Mean	SD	Mean	SD
Pollution						
Fine PM	65.176	44.555	48.111	28.797	82.272	50.587
Coarse PM	265.039	187.236	278.751	219.217	251.303	147.168
Production						
Hourly Efficiency	49.604	19.852	50.521	19.800	48.686	19.862
	Observations		Mean		SD	
Supervisor Characteristics						
1(Experience >= 1.5 yrs)	820588		0.551		0.497	
1(Relatability Index = 4)	820588		0.248		0.432	
1(Age >= 33)	860804		0.570		0.495	
1(Native Language = Kannada)	820588		0.852		0.305	
1(Education <= 10th Standard)	820588		0.583		0.493	
1(Native City = Bangalore)	820588		0.919		0.273	

matter level, FPM, on floor f for hour h on day d in month m on worker hourly efficiency E. We estimate equation 9 in both levels of efficiency as well as logs in which we replace E with $\ln(E)$. CPM is coarse PM on floor f for hour h on day d in month m. γ_h are hour fixed effects; η_m are month fixed effects; and $\delta_d$are day-of-week fixed effects. In additional specifications, we also include line fixed effects α_l and/or worker fixed effects α_i.

We then also estimate non-linearities in the gradient by fitting separate slopes for each quartile of the distribution of fine PM. Specifically, we estimate the following amended specification:

$$E_{ihdm} = \alpha_0 + FPM_{fhdm}\Big[\sum_{j=1}^{4}\beta_j Q(j)_{fhdm}\Big] + \phi CPM_{fhdm} + \gamma_h + \eta_m + \delta_d + \varepsilon_{ihdm} \tag{10}$$

Here, $Q(j)_{fhdm}$ are dummy variables taking value 1 if FPM_{fhdm} falls in the jth quartile of the fine PM distribution and β_j measure the jth quartile-specific slope coefficient on FPM_{fhdm}.

In the remaining specifications estimated below, we include supervisor characteristics along with their interactions with fine particulate matter levels. These specifications estimate the degree to which the impact of fine PM on efficiency differs by line supervisors. Specifically, we estimate the following amended specifications:

$$E_{ihdm} = \alpha_0 + \lambda(FPM_{fhdm} \times S_{ldm}) + \beta FPM_{fhdm} + \psi S_{ldm} + \phi CPM_{fhdm} + \gamma_h + \eta_m + \delta_d + \varepsilon_{ihdm} \tag{11}$$

$$\begin{aligned} E_{ihdm} \;&=\; \alpha_0 + (FPM_{fhdm} \times S_{ldm})\Big[\sum_{j=1}^{4}\lambda_j Q(j)_{fhdm}\Big] + FPM_{fhdm}\Big[\sum_{j=1}^{4}\beta_j Q(j)_{fhdm}\Big] \\ &\quad + \psi S_{ldm} + \phi CPM_{fhdm} + \gamma_h + \eta_m + \delta_d + \varepsilon_{ihdm} \end{aligned} \tag{12}$$

Here, λ and λ_j are the coefficients of interest and S_{ldm} is one of two key supervisor characteristics studied below: experience and relatability. We define experienced supervisors as those with greater than 1.5 years of experience as that is the median amongst the supervisors in the sample. We define relatable supervisors as those meeting all of the following 4 characteristics: younger than median age among supervisors, completed less than high school education, native tongue is the local language of the factory (Kannada), originally from the Bangalore area. These are meant to capture the degree to which the line supervisor is similar in age, education, and culture to the majority of the workers on the line.

Finally, we also estimate equations 9 through 12 replacing outcome E_{ihdm} with TC_{ihdm}, a dummy taking value 1 if worker i was assigned to a different task in hour h than she was in hour $h-1$. The corresponding estimates then of the β's and λ's reflect the degree to which workers are adjusted in response to fine PM levels and how much this response differs across supervisors of varying experience and relatability, respectively.

6 Results

In this section, we present and discuss the results of the empirical analysis described in section 5 above.

6.1 Impacts of Fine PM on Worker Efficiency

We begin by establishing the existence of a gradient between efficiency and contemporaneous exposure to fine PM. We first present graphical evidence of this gradient, and follow with tables reporting the regression analogues to the exercises conducted in the figures.

As depicted in Figures 1A-1F, some coincidental patterns across month, day of week, and hour of day exist in both worker efficiency and levels of fine particulates. Accordingly, we include, as discussed in section 5, month of year, day of week, and hour of day dummies in all empirical specifications that follow. Similarly, all figures below depict residuals from regressions of efficiency on these baseline fixed effects. We also include additional controls and fixed effects in alternate specifications to explore robustness and consistency of results.

Figures 2A and 2B plots hourly efficiency residuals in levels and logs, respectively, against hourly fine PM levels with the vertical dashed line representing the mean fine PM residual value corresponding to the mean level in California. The solid gradient is the residual from a base specification including month, day of week, and hour of day fixed effects; while the dashed line is the residual from a specification including production line fixed effects, and the dotted line from a specification including both line and worker fixed effects. All six plots across both figures depict identical negative, yet non-linear gradients. The slope appears particularly negative at low levels of fine PM, becoming progressively less negative towards the high end of the fine PM distribution. Overall the slope shows that an increase in fine PM levels of roughly 50 micrograms/cubic meter (just over 1 standard deviation of the fine PM distribution) leads to a reduction in efficiency of roughly 2.5 percentage points (Figure 2A) or roughly 5 percent (Figure 2B).

Figure 2A

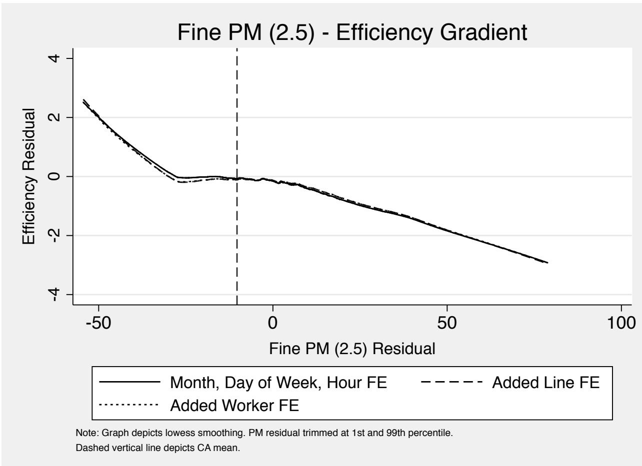
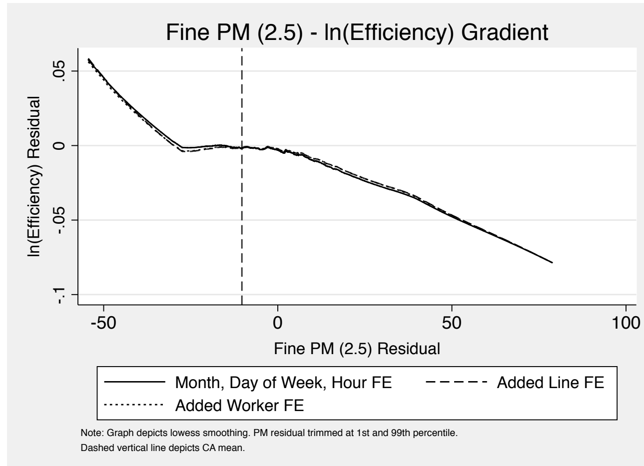


Figure 2B



In Table 2, we report estimates from regression analysis analogous to the figures discussed above. Columns 1 through 3 of Panel A report results from the estimation of equation **??**. A one $\mu g/m^3$ increase in fine PM (reported in the first row) leads to a decrease in individual hourly efficiency of roughly .03 percentage points. Fine PM has a standard deviation of roughly 45 (as reported in Table 1). The second row of Table 2 reports that a one SD rise in fine PM leads to a decrease in individual hourly efficiency of between 1.42-1.45 percentage points. Columns 4 through 6 report similar estimates in logs instead of levels. A one $\mu g/m^3$ increase in fine PM leads to a reduction of .08%; while a one SD rise in fine PM leads to between a 3.56-3.67% reduction in hourly worker efficiency. As discussed in section 5, we try three separate regression specifications at the worker level. The first includes, in addition to coarse PM level, only time fixed effects, namely, hour of the day, day of the week, and month fixed effects. The second adds worker fixed effects in addition to the controls in the first specification, and the third includes both individual worker and line fixed effects to the baseline specification.

In Panel B of Table 2, we report estimates from equation 10 in which we fit linear slopes separately by quartile of the fine PM distribution. Columns 1 through 3 show that, as indicated in Figure 2A, the slope of the gradient is most steeply negative in the first quartile of the fine PM distribution (between -2.4 and -2.6), slightly less steep through the second and third quartiles (between -2 and -2.4), and flattest in the fourth quartile (between -1.8 and -1.9). Columns 4 through 6 of Panel B show the same

Table 2

Impact of Pollution on Production Efficiency

	(1)	(2)	(3)	(4)	(5)	(6)
	Efficiency			ln(Efficiency)		
Panel A: Linear Effects	(Actual Production / Targeted Production)			ln(Actual Production / Targeted Production)		
Fine PM	-0.03259***	-0.03219***	-0.03186***	-0.00082***	-0.00080***	-0.00080***
	(0.00181)	(0.00173)	(0.00171)	(0.00005)	(0.00005)	(0.00005)
Standardized Fine PM	-1.45203***	-1.43407***	-1.41953***	-0.03668***	-0.03575***	-0.03563***
	(0.08086)	(0.07726)	(0.07621)	(0.00215)	(0.00210)	(0.00207)
Coarse PM	0.00320***	0.00336***	0.00339***	0.00008***	0.00009***	0.00009***
	(0.00036)	(0.00036)	(0.00036)	(0.00001)	(0.00001)	(0.00001)
Panel B: PM Quartiles						
1st Quartile Std Fine PM	-2.58035***	-2.52083***	-2.42249***	-0.07033***	-0.06822***	-0.06605***
	(0.20092)	(0.19681)	(0.19405)	(0.00549)	(0.00543)	(0.00537)
2nd Quartile Std Fine PM	-2.40853***	-2.34758***	-2.26508***	-0.06122***	-0.05939***	-0.05752***
	(0.15950)	(0.15553)	(0.15285)	(0.00446)	(0.00440)	(0.00434)
3rd Quartile Std Fine PM	-2.09688***	-2.02599***	-1.95282***	-0.05391***	-0.05165***	-0.05000***
	(0.14385)	(0.14032)	(0.13793)	(0.00393)	(0.00387)	(0.00382)
4th Quartile Std Fine PM	-1.87873***	-1.84661***	-1.80148***	-0.04921***	-0.04789***	-0.04702***
	(0.11457)	(0.11159)	(0.10973)	(0.00317)	(0.00313)	(0.00309)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	No	Yes	Yes
Worker FE	No	No	Yes	No	No	Yes
Observations	860,804	860,804	860,804	860,804	860,804	860,804
Mean of Dependent Variable	49.60439	49.60439	49.60439	3.803626	3.803626	3.803626

Notes: Robsut standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level.

pattern in logs, as depicted in Figure 2B, with slopes ranging from negative 7% per SD increase in fine PM in the first quartile to a reduction of roughly 4.8% per SD fine PM increase in the fourth quartile of the fine PM distribution.

6.2 Heterogeneous Impacts by Workers and Lines

Having established a negative and somewhat convex pollution-productivity gradient, we next explore the degree to which the slope of this gradient varies by worker and line. The model set forth in section 3 imposes heterogeneous impacts of pollution on workers (or more specifically, worker-task matches) and finds heterogeneous impacts by lines (or rather supervisors) as a result of the dynamic worker-task match optimization process. Here we check whether the data supports such a characterization.

Figure 3A plots the pollution-ln(efficiency) gradient from Figure 2B, but separately by the baseline efficiency level of the worker within the line. That is, we first categorize workers into quartiles of the efficiency distribution within the line during hours with low fine PM levels (within the first quartile of the fine PM distribution), and then draw gradients of the evolution of their efficiency over the fine PM distribution for each quartile separately.[5] The gradients in Figure 3A show that indeed the slopes are different for workers of different baseline efficiency levels in the line, with the most efficient workers at baseline being the most impacted the least efficient workers at baseline nearly unaffected.

Figure 3B repeats the exercise from Figure 3A, but for task difficulty quartiles instead of baseline worker efficiency quartiles. That is, we first categorize operations or tasks into quartiles of efficiency on low PM days as a measure of the task's difficulty. We do so using residuals from specifications regressing efficiency on coarse PM, month, day of week, and hour fixed effects as well as line and worker fixed effects. In this sense, the categorization of tasks to difficulty levels should be void of line or worker specific contributions to, along with fine PM impacts on, efficiency levels. The comparison of the gradients by quartile of task difficulty in Figure 3B show that the most difficult tasks are more taxed by fine PM levels than are less difficult tasks, with the simplest tasks appearing unaffected or even positively impacted by high fine PM levels. This positive impact on simple tasks could reflect reallocations of workers across tasks in response to high PM levels as proposed by the model in section 3.

If reallocation is indeed occurring within the line, and some line supervisors are better at, or more

[5] Mapping to baseline efficiency quartiles are done using residuals from the baseline specification including coarse PM and month, day of week, and hour of day fixed effects.

likely to undertake, this reallocation than others, then we should expect that the slopes of the pollution-efficiency gradient are heterogeneous across lines. In Figure 3C, we check for this heterogeneity by plotting the pollution-productivity gradient for each line separately. Indeed, Figure 3C shows clearly that some lines have steep negative gradients quite similar to that depicted in Figure 2B, while others have gradients that are nearly flat or concave in shape. In the following sections, we report results from further regression analysis aimed at explaining this heterogeneity across lines.

Figure 3A

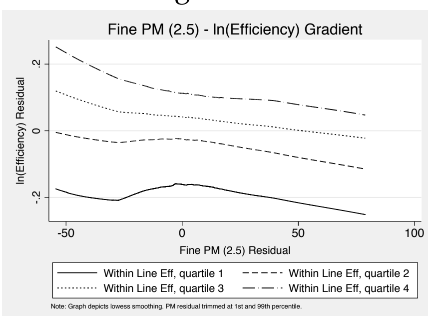


Figure 3B

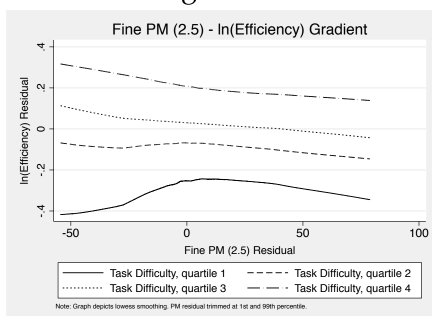
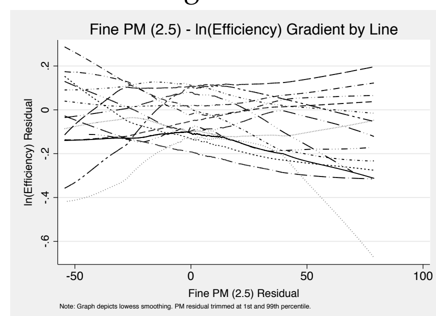


Figure 3C



6.3 Impacts of Fine PM on Efficiency by Supervisor Characteristics

We begin our investigation of the role of supervisors in mitigating the impacts of fine PM on efficiency by drawing the pollution-efficiency gradients for lines under the supervision of more experiences supervisors and less experienced supervisors separately. This comparison is depicted in Figure 4 and clearly shows that workers on lines with more experienced supervisors (those with greater than or equal to 1.5 years of tenure with the factory) have a less steeply negative gradient than those with less experienced supervisors.

Figure 5 repeats the same exercise for more "relatable" supervisors. Here, we define "relatable" supervisors (as described in section 5) as those who are relatively young and uneducated and whose native language and city Kannada and Bangalore, respectively. Once again, we find in Figure 5 that the efficiency of workers on lines with more relatable supervisors is much less impacted by fine PM exposure than that of lines and workers with less relatable supervisors.

Table 3 reports estimation results from the analogous regression analysis to the exercise undertaken in Figure 4. Once again, Panel A reports results from linear specifications in which estimates in the

Figure 4

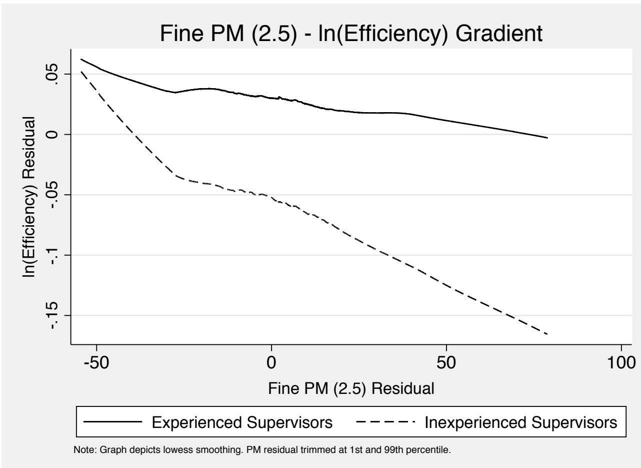
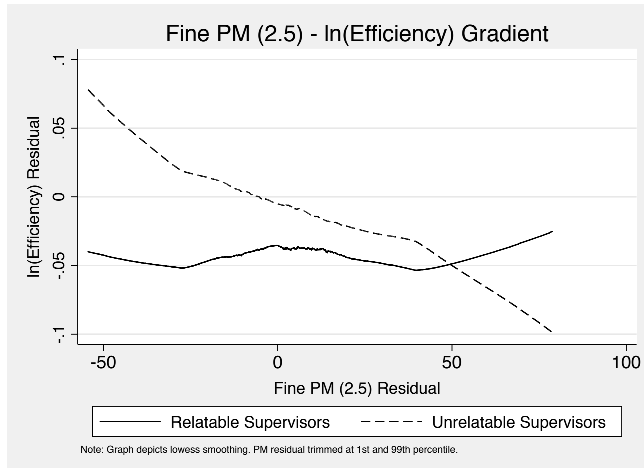


Figure 5



second row slopes among workers on lines with inexperienced supervisors; while estimates in the first row measure how slopes among those with experienced supervisors deviate from those in the second row. As in previous tables, Panel B shows estimates of quartile-specific slopes for workers on lines with inexperienced supervisors (bottom four rows in Panel B) and deviations from these slopes for those with more experienced supervisors (top four rows in Panel B). As before, columns 1 through 3 show estimates for efficiency in levels, while columns 4 through 6 show estimates for efficiency in logs.

In Panel A, we find that having a more experienced supervisor mitigates the impact of fine PM on efficiency by between 22 and 35%. Panel B shows that the largest mitigation (roughly 35-40%) occurs in the second quartile with still a significant degree of mitigation occurring in the third and particularly the fourth quartiles of the fine PM distribution. However, there is no evidence of significant mitigation occurring in the first quartile. These patterns suggest that supervisors, and specifically their experience levels, contribute to the non-linearities in the pollution-productivity gradient depicted in Figures 2A and 2B and estimated in Table 2.

Table 4 reports estimates of heterogeneity from supervisor relatability interaction specifications identical to those represented in Table 3 for supervisor experience. Here, we find in Panel A that having a highly relatable supervisor mitigates the impact of fine PM on efficiency by between 50 and 80%. Panel B once again shows that there is far less mitigation at first quartile fine PM levels than at higher levels, and the largest degree of mitigation occurs in the middle of the distribution at second and third quartile levels.

Table 3
Heterogeneous Impacts of Pollution on Production Efficiency by Supervisor Experience

	(1)	(2)	(3)	(4)	(5)	(6)
	Efficiency (Actual Production / Targeted Production)			ln(Efficiency) ln(Actual Production / Targeted Production)		
Panel A: Linear Effects						
Experienced Supervisor x Std Fine PM	0.62434***	0.63587***	0.37305*	0.01199**	0.01278**	0.00845*
	(0.23681)	(0.21961)	(0.21421)	(0.00541)	(0.00511)	(0.00492)
Standardized Fine PM	-1.85538***	-1.79527***	-1.63073***	-0.04322***	-0.04156***	-0.03898***
	(0.16639)	(0.15240)	(0.15034)	(0.00405)	(0.00379)	(0.00375)
Experienced Supervisor	2.00563***		-5.68738	0.06474***		-0.13086
	(0.52008)		(4.80423)	(0.01240)		(0.11776)
Panel B: PM Quartiles						
Experienced x 1st Quartile Std Fine PM	0.44311	0.22286	-0.21670	-0.00559	-0.00861	-0.01539
	(0.44494)	(0.41968)	(0.41785)	(0.01017)	(0.00974)	(0.00956)
Experienced x 2nd Quartile Std Fine PM	1.21374***	1.05405***	0.56989*	0.01880**	0.01717**	0.00937
	(0.33889)	(0.31669)	(0.31102)	(0.00789)	(0.00751)	(0.00727)
Experienced x 3rd Quartile Std Fine PM	0.61359**	0.51511*	0.11941	0.00678	0.00562	-0.00113
	(0.30356)	(0.28452)	(0.28116)	(0.00689)	(0.00658)	(0.00641)
Experienced x 4th Quartile Std Fine PM	0.62089***	0.64228***	0.38075*	0.01242**	0.01329***	0.00869*
	(0.23077)	(0.21508)	(0.21367)	(0.00529)	(0.00502)	(0.00492)
1st Quartile Std Fine PM	-2.83790***	-2.53543***	-2.17487***	-0.06379***	-0.05719***	-0.05087***
	(0.33735)	(0.31666)	(0.31360)	(0.00843)	(0.00807)	(0.00800)
2nd Quartile Std Fine PM	-3.08830***	-2.82880***	-2.46074***	-0.06856***	-0.06313***	-0.05658***
	(0.26189)	(0.24551)	(0.24042)	(0.00667)	(0.00639)	(0.00628)
3rd Quartile Std Fine PM	-2.49209***	-2.26769***	-1.96179***	-0.05660***	-0.05124***	-0.04558***
	(0.23557)	(0.22054)	(0.21622)	(0.00583)	(0.00557)	(0.00548)
4th Quartile Std Fine PM	-2.26124***	-2.16757***	-1.96932***	-0.05477***	-0.05219***	-0.04860***
	(0.18694)	(0.17262)	(0.17113)	(0.00475)	(0.00449)	(0.00447)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	No	Yes	Yes
Worker FE	No	No	Yes	No	No	Yes
Observations	820,588	820,588	820,588	820,588	820,588	820,588
Mean of Dependent Variable	49.72143	49.72143	49.72143	3.804172	3.804172	3.804172

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level.

Table 4
Heterogeneous Impacts of Pollution on Production Efficiency by Supervisor Relatability

	(1)	(2)	(3)	(4)	(5)	(6)
	Efficiency			ln(Efficiency)		
Panel A: Linear Effects	(Actual Production / Targeted Production)			ln(Actual Production / Targeted Production)		
Relatable Supervisor x Std Fine PM	0.79141***	1.37193***	0.94430***	0.02797***	0.03733***	0.02713***
	(0.25248)	(0.22795)	(0.21482)	(0.00588)	(0.00562)	(0.00514)
Standardized Fine PM	-1.62605***	-1.78794***	-1.66236***	-0.04146***	-0.04396***	-0.04119***
	(0.09867)	(0.09204)	(0.08803)	(0.00245)	(0.00233)	(0.00222)
Relatable Supervisor	-2.71434***		3.30166	-0.08583***		0.01142
	(0.57893)		(2.44139)	(0.01409)		(0.05930)
Panel B: PM Quartiles						
Relatable x 1st Quartile Std Fine PM	0.22318	1.70163***	0.74646*	0.02393**	0.04959***	0.02726***
	(0.46802)	(0.42540)	(0.40779)	(0.01088)	(0.01042)	(0.00964)
Relatable x 2nd Quartile Std Fine PM	1.32855***	2.25123***	1.41806***	0.04635***	0.06133***	0.04140***
	(0.36004)	(0.32620)	(0.30883)	(0.00846)	(0.00807)	(0.00741)
Relatable x 3rd Quartile Std Fine PM	1.20146***	1.93550***	1.27851***	0.04195***	0.05352***	0.03798***
	(0.32858)	(0.29965)	(0.28510)	(0.00767)	(0.00738)	(0.00683)
Relatable x 4th Quartile Std Fine PM	0.74035***	1.32272***	0.90639***	0.02650***	0.03601***	0.02621***
	(0.24886)	(0.22606)	(0.21646)	(0.00579)	(0.00557)	(0.00517)
1st Quartile Std Fine PM	-2.48170***	-2.81407***	-2.46804***	-0.06855***	-0.07399***	-0.06606***
	(0.23450)	(0.22657)	(0.22032)	(0.00611)	(0.00595)	(0.00577)
2nd Quartile Std Fine PM	-2.58796***	-2.78380***	-2.48318***	-0.06563***	-0.06856***	-0.06148***
	(0.18667)	(0.17910)	(0.17177)	(0.00492)	(0.00478)	(0.00457)
3rd Quartile Std Fine PM	-2.31102***	-2.44600***	-2.20384***	-0.05963***	-0.06116***	-0.05552***
	(0.16398)	(0.15730)	(0.15223)	(0.00422)	(0.00408)	(0.00393)
4th Quartile Std Fine PM	-1.98507***	-2.12673***	-1.97426***	-0.05134***	-0.05347***	-0.05009***
	(0.12871)	(0.12368)	(0.11970)	(0.00339)	(0.00330)	(0.00319)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	No	Yes	Yes
Worker FE	No	No	Yes	No	No	Yes
Observations	820,588	820,588	820,588	820,588	820,588	820,588
Mean of Dependent Variable	49.72143	49.72143	49.72143	3.804172	3.804172	3.804172

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level.

We next investigate the mechanism by which this active mitigation on the part of the supervisor might occur and present further empirical evidence in support of the model.

6.4 Worker-Task Match Adjustment Responses to Fine PM

Figures 6 and 7 repeat the exercises from Figures 4 and 5, respectively, replacing worker hourly efficiency on the y axis with the probability that a worker is reallocated to another task each hour. That is, we define task match adjustment as a dummy taking value 1 if a worker is assigned to a different task this hour than the task she was assigned to in the previous hour. As predicted by the model, both Figures 6 and 7 show that the probability of task match adjustment is increasing in fine PM levels (and seemingly in deviations from mean fine PM levels as we would suspect if the mean fine PM levels determine supervisors ex ante optimal work-task match solutions) and much more strongly for workers with more experienced and relatable supervisors.

Figure 6

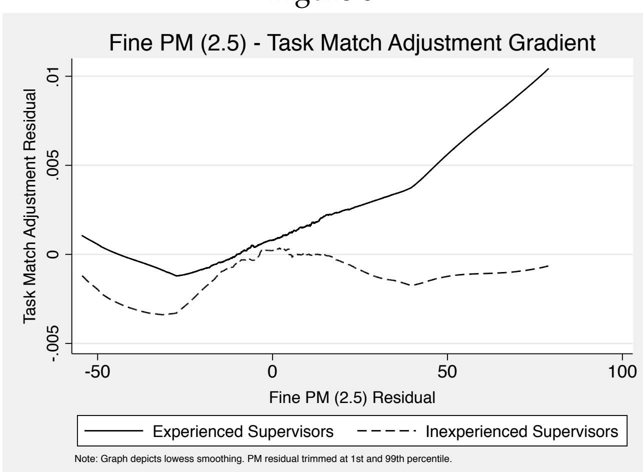
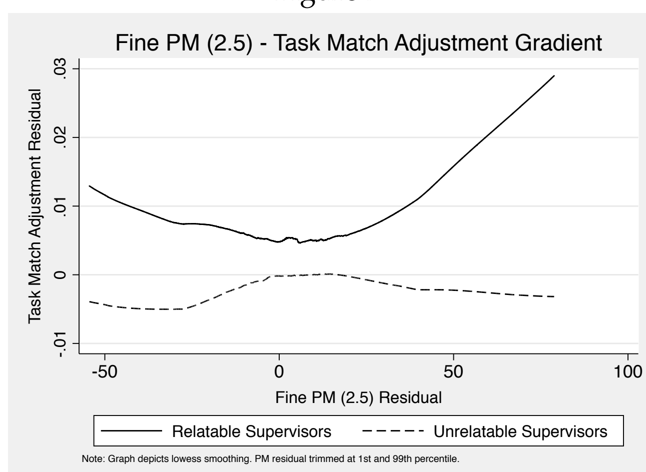


Figure 7



Once again, Tables 5 and 6 present estimates from analogous regression analysis to the exercises conducted in Figures 6 and 7, respectively. As in Tables 3 and 4, Panels A report linear and continuous interactions, while Panels B report quartile-specific slopes and supervisor-specific deviations from each quartile-specific slope. Here, however, though columns 1 through 3 of Tables 5 and 6 are from specifications identical to those represented in columns 1 through 3 of Tables 3 and 4, we include an additional specification in columns 4 of Tables 5 and 6 in which we add garment style by line by day fixed effects to the baseline month, day of week, and hour of day fixed effects. This specification is meant to isolate task match adjustments within line and garment order on a given day (which are most likely to reflect conscious production decisions on the part of the supervisor) from adjustments across lines or garment styles within the day (which would reflect completion of an order or manpower shortages elsewhere on the production floor or some other unrelated shock). Note that these additional fixed effects subsume the line fixed effects from the specification represented in column 2, but do not include the worker fixed effects in the specification represented in column 3 for the sake of parsimony.

In Panel A of both Tables 5 and 6, we find that there is little evidence of a relationship between fine PM levels and worker-task match adjustment on lines with inexperienced or less relatable supervisors, but there is a strong, positive impact of fine PM on adjustments for workers with more experienced and highly relatable supervisors. Specifically, a one SD increase in fine PM levels leads to between a .23 and .58 percentage point increase in the probability that each worker on a line under the supervision of an experienced supervisor is reallocated across tasks each hour (from a mean of roughly 15 percent). This impact for workers with highly relatable supervisors is between .23 and .72 percentage points.

Panel B of Table 5 shows that adjustment responses to fine PM levels among experienced supervisors are largest in the third and fourth quartiles with the least adjustment occurring in the first quartile; however, we find some evidence of large adjustments at first quartile PM levels in the specifications reported in columns 1 and 4. On the other hand, Panel B of Table 6 shows that worker-task match adjustment responses among highly relatable supervisors are strongest at first and second quartile levels of fine PM with some evidence of large adjustments in the fourth quartile in specifications reported columns 3 and 4.

These patterns of adjustments are consistent with the patterns of heterogeneous impacts on efficiency presented in Tables 3 and 4, and further support the predictions of the model. We, therefore, interpret these additional results are strong evidence in support of the mechanisms proposed and predictions developed in section 3 above.

Given that we see workers completing many different tasks across different hours and days, we can actually observe the degree to which individual workers indeed get reallocated to tasks which they find easier or on which they can achieve higher efficiency as the fine PM level deviates from mean levels. We first use data from low fine PM hours and days to rank tasks for each worker by the mean efficiency level that the worker achieves on each task. That is, for each worker the task ranked 1 is the task on which that worker achieves the lowest mean efficiency during low PM levels; the task ranked 2 is the task on which the worker achieves the second lowest mean efficiency during low PM levels;

Table 5

Impacts of Pollution on Task Match Adjustment by Supervisor Experience

	(1)	(2)	(3)	(4)
	Worker-Task Match Change			
Panel A: Linear Effects	1(Worker Switched Tasks from Last Hour)			
Experienced Supervisor x Std Fine PM	0.00582***	0.00376***	0.00230**	0.00383***
	(0.00135)	(0.00113)	(0.00095)	(0.00097)
Standardized Fine PM	-0.00203**	-0.00120	-0.00030	-0.00057
	(0.00098)	(0.00087)	(0.00077)	(0.00070)
Experienced Supervisor	-0.00727***		0.01347	
	(0.00213)		(0.01425)	
Panel B: PM Quartiles				
Experienced x 1st Quartile Std Fine PM	0.00805***	0.00514**	0.00253	0.00439***
	(0.00251)	(0.00211)	(0.00175)	(0.00131)
Experienced x 2nd Quartile Std Fine PM	0.00827***	0.00565***	0.00342**	0.00369***
	(0.00192)	(0.00163)	(0.00136)	(0.00113)
Experienced x 3rd Quartile Std Fine PM	0.00747***	0.00522***	0.00323**	0.00340***
	(0.00176)	(0.00155)	(0.00132)	(0.00111)
Experienced x 4th Quartile Std Fine PM	0.00563***	0.00360***	0.00221**	0.00383***
	(0.00132)	(0.00111)	(0.00094)	(0.00097)
1st Quartile Std Fine PM	-0.00657***	-0.00520**	-0.00341*	-0.00128
	(0.00223)	(0.00208)	(0.00198)	(0.00140)
2nd Quartile Std Fine PM	-0.00579***	-0.00460***	-0.00308**	-0.00132
	(0.00179)	(0.00167)	(0.00156)	(0.00114)
3rd Quartile Std Fine PM	-0.00478***	-0.00385***	-0.00255*	-0.00094
	(0.00154)	(0.00143)	(0.00133)	(0.00099)
4th Quartile Std Fine PM	-0.00312***	-0.00229**	-0.00134	-0.00079
	(0.00121)	(0.00112)	(0.00105)	(0.00082)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	Yes
Worker FE	No	No	Yes	Yes
Observations	820,588	820,588	820,588	820,588
Mean of Dependent Variable	0.1503142	0.1503142	0.1503142	0.1503142

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level.

Table 6
Impacts of Pollution on Task Match Adjustment by Supervisor Relatability

	(1)	(2)	(3)	(4)
	Worker-Task Match Change			
Panel A: Linear Effects	1(Worker Switched Tasks from Last Hour)			
Relatable Supervisor x Std Fine PM	0.00717***	0.00439***	0.00226*	0.00357**
	(0.00188)	(0.00151)	(0.00127)	(0.00150)
Standardized Fine PM	-0.00071	-0.00019	0.00043	0.00062
	(0.00077)	(0.00071)	(0.00064)	(0.00059)
Relatable Supervisor	-0.00207		0.01264	
	(0.00207)		(0.00918)	
Panel B: PM Quartiles				
Relatable x 1st Quartile Std Fine PM	0.01421***	0.00934***	0.00461*	0.00360*
	(0.00382)	(0.00311)	(0.00248)	(0.00191)
Relatable x 2nd Quartile Std Fine PM	0.01182***	0.00824***	0.00409**	0.00225
	(0.00287)	(0.00238)	(0.00200)	(0.00162)
Relatable x 3rd Quartile Std Fine PM	0.00863***	0.00544**	0.00237	0.00213
	(0.00261)	(0.00221)	(0.00191)	(0.00169)
Relatable x 4th Quartile Std Fine PM	0.00710***	0.00438***	0.00234*	0.00355**
	(0.00185)	(0.00150)	(0.00128)	(0.00150)
1st Quartile Std Fine PM	-0.00571***	-0.00462**	-0.00315*	0.00023
	(0.00192)	(0.00183)	(0.00175)	(0.00128)
2nd Quartile Std Fine PM	-0.00422***	-0.00348**	-0.00219	0.00013
	(0.00151)	(0.00144)	(0.00137)	(0.00102)
3rd Quartile Std Fine PM	-0.00281**	-0.00223*	-0.00131	0.00037
	(0.00128)	(0.00122)	(0.00115)	(0.00087)
4th Quartile Std Fine PM	-0.00187*	-0.00135	-0.00069	0.00039
	(0.00100)	(0.00095)	(0.00091)	(0.00072)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	Yes
Worker FE	No	No	Yes	Yes
Observations	820,588	820,588	820,588	820,588
Mean of Dependent Variable	0.1503142	0.1503142	0.1503142	0.1503142

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level.

and so on. We observe a given worker on up to 30 tasks during low PM levels.

Figure 8 shows the relationship between the worker-specific task ranking and the mean efficiency the worker achieved at that rank task. Figure 9 shows that as fine PM levels deviate from mean levels, workers are indeed assigned to higher ranked (i.e., easier or higher efficiency) tasks. This pattern holds for all workers in the second, third, and fourth quartiles of baseline efficiency within the line. In fact, workers in the fourth quartile appear to be more likely to be reallocated to higher ranked tasks than are those in the second or third quartile. This pattern is consistent with the type of rank order reallocation of workers across tasks depicted in the model developed in section 3. However, workers in the first quartile of baseline efficiency do not appear to be as likely to be reallocated, perhaps because these workers are allocated to the most difficult tasks that many other workers cannot complete.

Figure 8

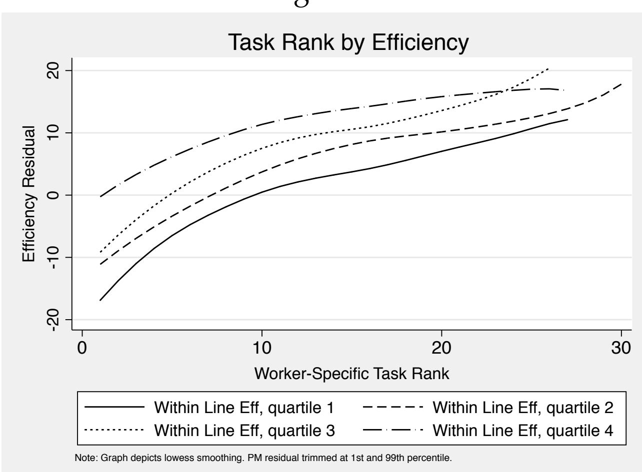
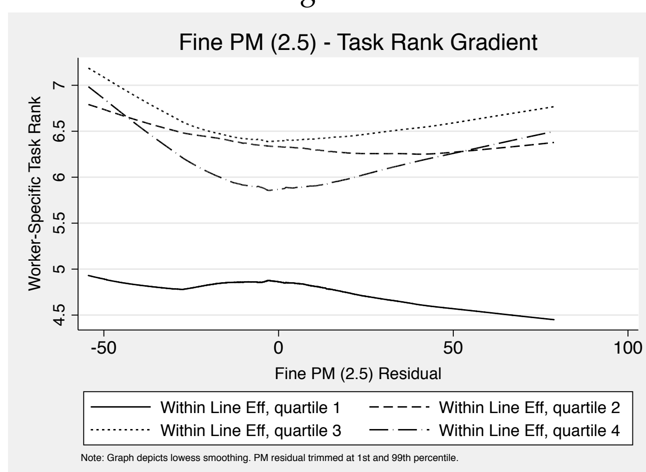


Figure 9



We finish our investigation of worker-task reallocations in response to heterogeneously taxed worker efficiency at higher fine PM levels check the degree to which these reallocations serve to offset the impacts of pollution and equalize production across workers in the line. Figure 10 repeats the exercise depicted in Figure 3A, but plotting baseline efficiency quartile specific gradients for workers with more and less experienced supervisors separately. Figure 11 does the same, but separately for workers with more and less relatable supervisors. Both Figures 10 and 11 show strong evidence of mitigation on the part of supervisors of impacts of fine PM exposure across the efficiency distribution.

Figure 10

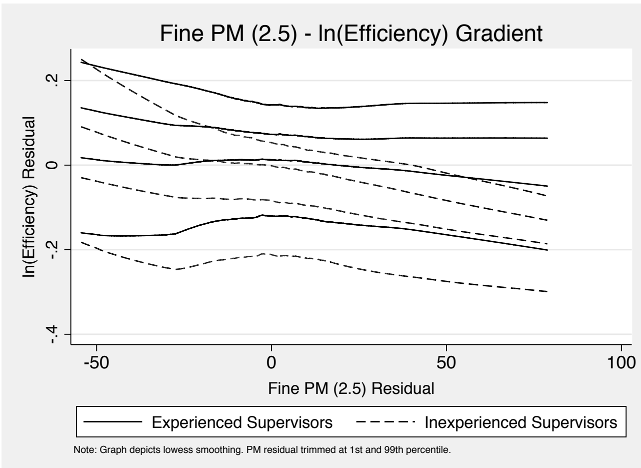
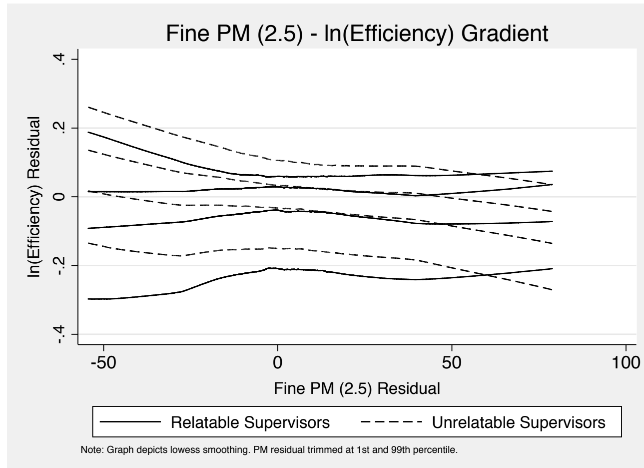


Figure 11



6.5 Impacts of Fine PM on Worker Attendance and Health Clinic Visits

Finally, we investigate whether exposure to fine PM levels are impacting efficiency through increases in absenteeism or foregone production time due to health clinic visits. Our interpretation of the results through the framework developed in section 3, particularly as pertains to the role of supervisors in worker-task match adjustments, relies on intensive margin impacts of fine PM exposure on worker-specific effort and efficiency. However, there might also be impacts of fine PM exposure on extensive margin outcomes such as worker attendance and health clinic visits.

Table 7 reports results from regressions of absenteeism and health clinic visits on contemporaneous standardized daily fine and coarse PM levels and the one day lags of these measures. Note that these regressions are conducted at the daily level as data on worker attendance and health clinic visits are recorded at the daily level rather than hourly level. Panel A reports results from these analyses conducted at the worker level across specifications including month and day of week fixed effects in columns 1 and 3 and additional worker fixed effects in columns 2 and 4.

Panel B reports results from similar analyses conducted at the unit level in which number of workers reporting absent and visiting the health are summed across the entire unit each day and then regressed in a time series regression on the same standardized daily fine and coarse PM levels as well as the one day lags of these measures. We also sum the number of workers reporting to work tardy each morning and those working late beyond regular working hours each day and regress these on daily fine and coarse PM levels and their one day lags as well. In Panel B, results for number of workers visiting the health clinic per day are reported in column 1; results for the number reporting absent per day are reported in column 2; results for number reporting tardy are presented in column 3; and results for number working over time are presented in column 4.

Across all results presented in both Panels A and B of Table 7, we find no evidence of impacts of either contemporaneous or daily lagged PM exposure on extensive margin measures of attendance and time spent producing on the line. This evidence supports our interpretation of pollution primarily impacting intensive margin effort and worker efficiency and the role of supervisors in reallocating workers to tasks in order to augment these impacts.

7 Conclusion

Pollution in urban centers of developing countries has skyrocketed in the last decade due to rapid industrial growth and lax regulation and enforcement related to emissions. Levels of pollution in developing country cities dwarf the levels in similarly sized developed country cities. The health costs of this pollution have been clearly shown in recent papers, but impacts on the labor force are only beginning to be explored.

In this study, we document a steep pollution-productivity gradient for particular matter pollution in garment factories in and around Bangalore, India. Productive efficiency is thus quite elastic with respect to PM2.5, the type of fine particulate matter pollution that is worst for respiratory health. Moreover, we find that management plays a key role in mediating this impact. In particular, workers with more skilled managers (those who are more experienced and "relatable") realize smaller declines in efficiency during high pollution hours and days. We show, using detailed, worker-operation-specific data that capable managers are able to reallocate workers across tasks in response to efficiency losses from high fine PM levels, and thus boost overall team productivity.

Our findings have important implications for environmental policy and firm decision-making in low-income countries. Policymakers should take into account the negative impacts of pollution on industrial output when crafting "green" legislation and allocating resources toward enforcement of existing laws related to industrial emissions. Firms, on the other hand, must take this pollution as a given and should act to mitigate its impacts on workers. Where air filtration and other pollution reduction measures are prohibitively costly, hiring skilled managers and optimizing the allocation of

Table 7
Impact of Pollution on Attendance and Health

Panel A: Worker-Level	(1)	(2)	(3)	(4)
	Absent		Visit Health Clinic	
Standardized Fine PM	0.00119	0.00053	-0.00033	-0.00032
	(0.00298)	(0.00294)	(0.00027)	(0.00026)
Standardized Daily Fine PM Lag	-0.00411	-0.00369	-0.00020	-0.00019
	(0.00283)	(0.00274)	(0.00028)	(0.00027)
Standardized Coarse PM	-0.00025	-0.00023	0.00005	0.00004
	(0.00203)	(0.00199)	(0.00019)	(0.00019)
Standardized Daily Coarse PM Lag	-0.00306	-0.00248	0.00024	0.00023
	(0.00214)	(0.00204)	(0.00019)	(0.00019)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Worker FE	No	Yes	No	Yes
Observations	630,153	630,153	547,462	547,462
Mean of Dependent Variable	0.1314712	0.1314712	0.0009371	0.0009371

Panel B: Unit-Level	# Visiting Health Clinic Per Day	# Absent Per Day	# Tardy Per Day	# Working Over Time Per Day
Standardized Fine PM	-0.74318	7.47782	8.46720	15.33834
	(0.55596)	(9.78940)	(19.79085)	(11.18281)
Standardized Daily Fine PM Lag	-0.41498	-6.02292	3.19599	5.81703
	(0.60940)	(9.14406)	(19.99067)	(11.09703)
Standardized Coarse PM	0.18926	-4.74490	12.33683	2.08001
	(0.46406)	(7.06202)	(18.73709)	(8.91204)
Standardized Daily Coarse PM Lag	0.59132	-5.07394	16.02090	2.72809
	(0.45819)	(7.04236)	(18.50304)	(10.57244)
Month, Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	247	247	247	247
Mean of Dependent Variable	2.003906	323.6211	640.125	471.3477

Notes: Robsut standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker leve in Panel A.

workers to tasks might allow firms to buffer negative productivity impacts ensuing from pollution exposure.

Furthermore, as exposure to high levels of air pollution is only one example of the myriad adverse productivity shocks that firms in developing countries face, our results on the impacts of these shocks and the role of management in navigating and mitigating these impacts can be generalized to help explain the vast labor and total factor productivity gaps that have been documented empirically in the literature and the role of managerial skill in reducing this gap. That is, we provide empirical evidence that adverse environmental conditions, in combination with shocks deriving from infrastructural failures (e.g., power outages, delays due to unmotorable roads and customs frictions) and input and manpower shortages, etc., might contribute significantly to the observed productivity gap between firms in developed and developing countries. Additionally, we support empirically the hypothesis recently proposed by the literature that management might also contribute to, or on the other hand help to reduce, this gap.

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A Checks and Robustness

In Figure A1, we plot fine and coarse PM levels across days of the week, including Sundays on which very little production occurs at the garment factory. We see that indeed fine PM continue to remain at roughly the same levels as those during the work week; while coarse PM drops measurably on Sundays, indicating that coarse PM is more likely produced through factory activity than fine PM. Figure A2 plots fine and coarse PM levels across hours of the day including non-production hours. Coarse PM shows high levels during production hours with a dip in levels before and after production hours as well as during lunch hours; while fine PM shows peaks during commuting hours and lower levels during peak production. These patterns suggest that coarse PM is more likely produced through garment manufacturing activity; while fine PM appears more likely to be produced through automobile exhaust during high traffic hours.

Figure A1:

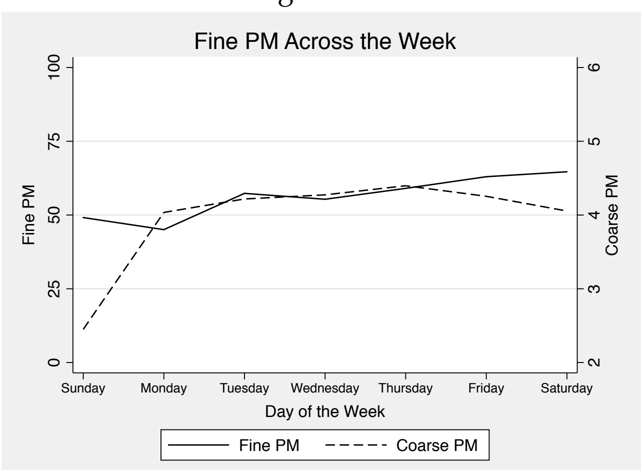
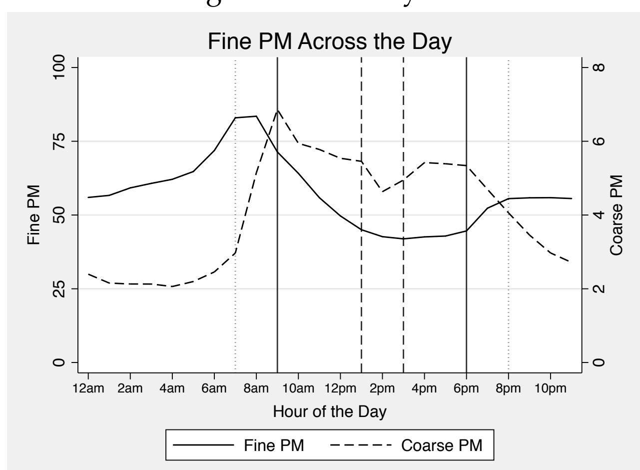


Figure A2: Hourly PM



Notes:

In Table A1, we report estimates from regression analogues to the comparisons depicted in Figure A2.

In Table A2, we check robustness of our main results to IV specifications in which contemporaneous fine PM levels are instrumented with levels one hour in the future after controlling for the day's fine PM average. The full pattern of results is overwhelmingly preserved.

In Table A3, we check robustness of our main results to including daily temperature as a control. Once again, the full pattern of results is preserved.

Table A1
Checks of Fine PM Exogeneity

	(1)	(2)
	Fine PM	Coarse PM
1(Production Hour)	-8.48976***	0.99862***
	(1.03569)	(0.11297)
1(Lunch Hour)	-0.47383	-0.41746***
	(0.62780)	(0.06411)
1(Commute Hour)	2.97599***	0.77616***
	(1.11590)	(0.09762)
1(Night Hour)	-1.61120	-0.49183***
	(1.22167)	(0.12377)
Day PM Average	0.00324***	0.00524***
	(0.00026)	(0.00019)
1 Hour Lag PM	0.00654***	0.00427***
	(0.00045)	(0.00019)
2 Hour Lag PM	0.00095***	0.00089***
	(0.00033)	(0.00020)
3 Hour Lag PM	-0.00003	-0.00023
	(0.00017)	(0.00018)
4 Hour Lag PM	-0.00070***	-0.00038***
	(0.00014)	(0.00012)
Month, Day-of-Week FE	Yes	Yes
Observations	5,150	5,150
Mean of Dependent Variable	56.69874	4.012719

Notes: Robsut standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the date level.

Table A2

Robustness to Instrumental Variables Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Efficiency (Actual Production / Targeted Production)				ln(Efficiency) ln(Actual Production / Targeted Production)				Worker-Task Match Change 1(Worker Switched Tasks from Last Hour)			
Relatable Supervisor x Std Fine PM*			0.83806***	1.47877***			0.03248***	0.04277***			0.00702***	0.00399***
			(0.27318)	(0.24591)			(0.00643)	(0.00617)			(0.00192)	(0.00155)
Relatable Supervisor			-3.14623***	8.12413***			-0.10184***	0.12010***			-0.00243	-0.02518***
			(0.61683)	(0.99501)			(0.01507)	(0.02337)			(0.00220)	(0.00682)
Experienced Supervisor x Std Fine PM*	0.54176**	0.53511**			0.00894	0.00930*			0.00568***	0.00323***		
	(0.25508)	(0.23765)			(0.00589)	(0.00559)			(0.00141)	(0.00115)		
Experienced Supervisor	2.08111***	7.46249***			0.06960***	0.17813***			-0.00689***	-0.03605***		
	(0.54748)	(0.94902)			(0.01312)	(0.02159)			(0.00228)	(0.00630)		
Standardized Fine PM*	-2.75725***	-2.90592***	-2.60698***	-2.98120***	-0.05720***	-0.06046***	-0.05883***	-0.06619***	0.00186	0.00386	0.00325	0.00468**
	(0.27838)	(0.26915)	(0.24100)	(0.24196)	(0.00660)	(0.00646)	(0.00591)	(0.00591)	(0.00244)	(0.00243)	(0.00236)	(0.00235)
Day's Average Fine PM	0.01245**	0.01848***	0.01341**	0.01843***	0.00020	0.00035**	0.00022	0.00034**	-0.00008	-0.00010**	-0.00008	-0.00010**
	(0.00558)	(0.00551)	(0.00553)	(0.00551)	(0.00014)	(0.00014)	(0.00014)	(0.00014)	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Coarse PM	0.00502***	0.00498***	0.00465***	0.00495***	0.00012***	0.00011***	0.00011***	0.00011***	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00041)	(0.00041)	(0.00041)	(0.00041)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker and Line FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722,039	722,039	722,039	722,039	722,039	722,039	722,039	722,039	722,039	722,039	722,039	722,039
Mean of Dependent Variable	49.33638	49.33638	49.33638	49.33638	3.795782	3.795782	3.795782	3.795782	0.1510417	0.1510417	0.1510417	0.1510417

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level. *All Fine PM measures and interactions of Fine PM with supervisor characteristics are instrumented using the Fine PM levels from one hour in the future, while controlling for the day's average Fine PM. All first stage coefficients are highly significant, with joint F-statistics well above conventionally accepted levels. First stage results are available upon request.

Table A3

Robustness to Climate Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Efficiency (Actual Production / Targeted Production)				ln(Efficiency) ln(Actual Production / Targeted Production)				Worker-Task Match Change 1(Worker Switched Tasks from Last Hour)			
Relatable Supervisor x Std Fine PM*			0.78731***	0.94122***			0.02781***	0.02701***			0.00688***	0.00205
			(0.25255)	(0.21481)			(0.00588)	(0.00514)			(0.00186)	(0.00126)
Relatable Supervisor			-2.70755***	3.29402			-0.08556***	0.01112			-0.00167	0.01199
			(0.57911)	(2.44110)			(0.01410)	(0.05929)			(0.00205)	(0.00946)
Experienced Supervisor x Std Fine PM*	0.62147***	0.36946*			0.01187**	0.00831*			0.00571***	0.00217**		
	(0.23690)	(0.21425)			(0.00542)	(0.00492)			(0.00135)	(0.00096)		
Experienced Supervisor	2.01064***	-5.68192			0.06495***	-0.13064			-0.00730***	0.01191		
	(0.52001)	(4.76762)			(0.01240)	(0.11624)			(0.00213)	(0.01414)		
Standardized Fine PM*	-1.85199***	-1.62664***	-1.62326***	-1.65954***	-0.04308***	-0.03882***	-0.04135***	-0.04109***	-0.00197**	-0.00025	-0.00065	0.00047
	(0.16634)	(0.15026)	(0.09873)	(0.08806)	(0.00405)	(0.00375)	(0.00245)	(0.00222)	(0.00098)	(0.00078)	(0.00078)	(0.00065)
Coarse PM	0.00320***	0.00316***	0.00288***	0.00315***	0.00008***	0.00008***	0.00007***	0.00008***	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00038)	(0.00037)	(0.00038)	(0.00037)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Additional Controls	**Daily Outdoor Temperature (NOAA)**											
Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker and Line FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	860,804	860,804	820,588	820,588	860,804	860,804	820,588	820,588	820,588	820,588	820,588	820,588
Mean of Dependent Variable	49.33638	49.33638	49.33638	49.33638	3.795782	3.795782	3.795782	3.795782	0.1510417	0.1510417	0.1510417	0.1510417

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the worker level. *All Fine PM measures and interactions of Fine PM with supervisor characteristics are instrumented using the Fine PM levels from one hour in the future, while controlling for the day's average Fine PM. All first stage coefficients are highly significant, with joint F-statistics well above conventionally accepted levels. First stage results are available upon request.