MANAGEMENT AND SHOCKS TO WORKER PRODUCTIVITY*

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Abstract

Differences in managerial quality likely contribute significantly to firm productivity gaps between firms in developed and developing countries. But how specifically does management affect productivity? We model one potential channel for this effect: good managers are better able to deal with shocks to worker productivity. We test the model's predictions in an Indian garment factory, using hourly data on worker and line productivity, rich survey measures of managerial quality, and exogenous variation in pollution exposure, an important shock to worker effort. We find that lines supervised by higher quality managers (those better at identifying and solving production issues in general, and those who specifically monitor production more frequently and are more likely to replace underperforming workers) are more productive and exhibit more frequent reallocation of workers across tasks. We also find that productivity suffers in response to higher pollution exposure, and that the frequency of task reallocation rises as pollution deviates from median levels. Moreover, lines supervised by higher quality managers suffer substantially smaller losses in the face of higher pollution exposure, by way of increased task reallocation. Finally, we validate our indices of managerial quality against a measure of supervisor TFP, and provide descriptive evidence of the specific practices, management styles, and personality traits that contribute to managerial quality.

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1 Introduction

Firms in poor countries are substantially less productive than firms in rich countries (Caselli, 2005; Hall and Jones, 1999). Measurement of management practices across countries reveals that the spatial distributions of productivity and the quality of management are strikingly similar (Bloom and Van Reenen, 2007). Moreover, emerging evidence demonstrates that at least part of this relationship is causal: improving managerial quality, at least in large firms, can generate considerable increases in productivity (Bloom et al., 2013).

Still, we have limited evidence on the specific mechanisms that drive this impact. Some recent work has begun to get inside the black box: Macchiavello et al. (2015) and Schoar (2014), for example, carried out randomized management interventions in garment-producing firms that focused on technical training and relationship management. In this study, we contribute evidence on a novel mechanism for the impacts of management: good managers are better able to deal with shocks to worker productivity. We model the ability of managers to reorganize production in response to heterogeneous shocks to their workers' costs-of-effort. Good managers devote more attention (or equivalently, exert more effort) toward monitoring their employees, and thus are able to make real-time adjustments to the allocation of workers to tasks, which mitigates the impacts of shocks to individual productivity. This mechanism fits into a growing literature on the consequences of managerial inattention (e.g., Ellison and Snyder (2014); Reis (2006)).

We test the model's predictions in the context of an Indian garment firm, using hourly data on worker and line productivity, rich survey measures of managerial quality, and exogenous variation in pollution exposure, an important shock to worker effort. We construct three indices of managerial quality: a production problem-solving index, a worker monitoring and reallocation index, and a combination of these two indices.[1] We find that lines supervised by higher quality managers – those better at identifying and solving production issues in general, and those who specifically monitor production more frequently and are more likely to replace underperforming workers – are more productive and exhibit more frequent reallocation of workers across tasks.

We also find that productivity suffers in response to higher pollution exposure, and that the frequency of task reallocation rises as pollution deviates from median levels. Moreover, lines supervised

[1] Management data on practices, style, and personality were collected using survey instruments adapted from recent work on measuring managerial quality (Bloom and Van Reenen, 2007) as well as other standard personality and work history modules.

by higher quality managers suffer substantially smaller losses in the face of higher pollution exposure, by way of increased task reallocation. Finally, we validate our indices of managerial quality against a measure of supervisor TFP, and provide descriptive evidence of the specific practices, management styles, and personality traits that contribute to managerial quality. In sum, we show that one important way in which managerial quality impacts productivity is through managers' roles in diagnosing and mitigating the deleterious impacts of worker productivity shocks.

This paper adds to a growing body of work in economics on the impacts of management (Bloom et al., 2013; Bloom and Reenen, 2011; Bloom et al., 2010b; Bloom and Van Reenen, 2010; Bruhn et al., 2010; Lazear et al., 2014; Schoar, 2014). We highlight an important but unexplored channel – managers' responses to shocks to production – through which managerial quality impacts productivity in labor-intensive manufacturing settings. This is made possible by the highly granular nature of our worker productivity data and the collection of management quality measures at the lowest (and perhaps most direct) level of production supervision.

We also contribute to the understanding of firm productivity in low-income countries (Bloom et al., 2010a; Syverson, 2011; Tybout, 2000). Two branches of this literature are relevant to our study. First, intra-firm barriers to productivity growth – such as ethnic and gender-related frictions (Hjort, 2014; Macchiavello et al., 2015; Marx et al., 2015), information asymmetries (Heath, 2011), and the misalignment of organizational incentives (Amodio and Martinez-Carrasco, 2015; Atkin et al., 2015) – are often salient in low-income contexts. Second, environmental and infrastructural factors (which are often tied to the environment) matter a great deal as well (Adhvaryu et al., 2015; Allcott et al., 2014; Dell et al., 2012; Sudarshan and Tewari, 2013).[2] We add to this literature estimates of the impacts of particulate matter pollution on worker productivity in a low-income country with pollution levels several times higher than means in many high-income country environments. We estimate a negative gradient between air pollution and worker productivity using high-frequency micro-data, and find that this gradient is steeper for more difficult tasks, consistent with evidence from the medical literature (e.g., Mills et al. (2005)).

The rest of the paper is organized as follows. Section 2 discusses the specific garment production process in the study factory and reviews the medical evidence on the impacts of pollution exposure. Section 3 develops a theoretical framework to formalize the role of management in responding to pro-

[2]A related literature focuses on the impacts of environmental factors on productivity and labor supply in more developed countries. See, for example, Chang et al. (2014); Graff Zivin and Neidell (2012); Hanna and Oliva (2016).

ductivity shocks and outlines testable implications of the model. Then, section 4 discusses our data sources and the construction of key variables and section 5 describes our strategy for empirically testing the predictions of the model. Section 6 describes the results of these tests, and 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 determining productivity, and the physiological impacts of air pollution exposure.

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 (Heath and Mobarak, 2015; 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). Our research partner 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 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 workers to supervisors is sufficiently dynamic (yet clearly observable), to allow for the study of the interaction between supervisors and workers experiencing productivity shocks.

2.2.1 Cutting

Pieces of fabric needed for each segment of the garment are cut using patterns from a single sheet so as to perfectly match 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.

2.2.2 Sewing

Garments in this factory 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 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).[3] 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.

2.2.3 Finishing

In finishing, garments are checked, ironed, and packed for shipping. Most 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 packing. Orders are then packed and sent to port.

2.3 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 gar-

[3] 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.

ment complexity, order sizes, and delivery dates and production timelines, the supervisors of each line must adjust the worker composition of the line to optimize the garment-specific productivity subject to continually evolving manpower constraints. 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 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 more complex tasks. 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 management), "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.

2.4 Physiology of the Pollution-Productivity Gradient

A large body of studies 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 Model

3.1 Setup

There are two tasks and two workers. Labor is indivisible, meaning a worker can only be devoted to one task at a time. Let e_{ik} denote the effort given by worker i to task k.[4]

The output from task 1 (q_1) is given as

$$q_1 = h(e_{i1})$$

and the output from task 2 is given as,

$$q_2 = \tilde{g}(q_1, e_{2j}) = g(e_{i1}, e_{j2})$$

where subscript i, j denote the two workers and $h' > 0, h'' < 0, h''' < 0, \tilde{g}_1 > 0, \tilde{g}_2 > 0, \tilde{g}_{11} < 0, \tilde{g}_{22} < 0, \tilde{g}_{111} < 0, \tilde{g}_{222} < 0, \tilde{g}_{12} > 0, \tilde{g}(0, e) = 0 \quad \forall e$. The final output Q is equal to q_2. Note that conditional on effort, output of each task does not depend on the identity of the worker. Also, because labor is indivisible and q_2 depends on q_1, each task will be assigned one worker.

The worker's problem

Now consider the workers problem. Worker i receives a benefit (wage) of $b \cdot q_k$ where q_k is the output from the task which he is assigned.[5] However, the worker experiences a disutility $c(e + \gamma_i \delta)$ from

[4]We focus on two workers and two tasks for simplicity of exposition but the results can be generalized to $k > 2$.

[5]Though workers are paid a fixed base salary in our empirical context, they are eligible to earn daily production incentive

exerting effort e, with $c' > 0, c'' > 0$. Suppose without loss of generality that $\gamma_1 > \gamma_2$.[6] This utility cost depends in part on the level of a shock parameter δ, which is determined stochastically and is drawn from the distribution $F(\delta)$ with $E[\delta] = 0$. The worker observes (or, perhaps we should say "feels") δ.[7]

Then given δ worker i assigned to task 1 solves

$$\max_{e_{i1}} \quad bh(e_{i1}) - c(e_{i1} + \gamma_i \delta)$$

f.o.c.

$$bh'(e_{i1}) - c'(e_{i1} + \gamma_i \delta) = 0$$

s.o.c.

$$bh''(e_{i1}) - c''(e_{i1} + \gamma_i \delta) < 0$$

Since f is concave and and c is convex the second order condition holds. Worker i assigned to task 2 solves

$$\max_{e_{i2}} \quad bg(e_{j1}, e_{i2}) - c(e_{i2} + \gamma_i \delta)$$

f.o.c.

$$bg_2(e_{j1}, e_{i2}) - c'(e_{i2} + \gamma_i \delta) = 0$$

Thus solving the workers optimization problem we can solve for the workers optimal effort level as a function of the shock parameter $\{(e^*_{11}(\delta), e^*_{12}(\delta)), (e^*_{21}(\delta), e^*_{22}(\delta)\}$.

The supervisor's problem

The supervisor can choose the allocation of the tasks to each worker. He can choose between two orderings $g^1 \equiv g(e_{11}, e_{22})$ or $g^2 \equiv g(e_{21}, e_{12})$. He is paid a fixed multiple of his line's output, which for simplicity we assume is 1 in the exposition below.[8]

bonuses. We abstract away from this feature of the employment contract and approximate the benefit to the worker as a piece rate for simplicity, but the main predictions of the theory are unaltered by this simplification.

[6]We omit the case $\gamma_1 = \gamma_2$ because all worker heterogeneity would be eliminated in this case.

[7]We develop the model for a general shock-to-effort parameter, and test the model's implications using high-frequency variation in pollution levels as an empirical analog to this shock.

[8]The supervisor's contract in our empirical context is similar to the worker's contract, which includes a base salary plus daily bonus based on line production.

Perfect information benchmark

First consider the perfect information case (δ is known to the supervisor) as a benchmark. Then, given δ the supervisor solves

$$g^*(\delta) = \max\{g^1(\delta), g^2(\delta)\}$$

The output of the line will equal $g^*(\delta)$.

Imperfect information

Now suppose that the supervisor can only observe δ if he pays a (disutility of effort) cost of monitoring, denoted λ. If he chooses to not pay λ, then he will choose the ordering that maximizes output in expectation. Thus he solves,

$$g^E = \max\{Eg^1, Eg^2\}$$

where $Eg^1 \equiv \int g^1(\delta)dF(\delta)$, and $Eg^2 \equiv \int g^2(\delta)dF(\delta)$ respectively. Suppose that $Eg^2 < Eg^1$.

If, on the other hand, he does choose to expend the monitoring cost, then he observes δ and thus chooses $g^*(\delta)$.

Given this setup, the supervisor will choose to monitor and expend λ iff

$$\int g^*(\delta)dF(\delta) - g^E > \lambda$$

. We call a "good supervisor" someone with a monitoring cost small enough that he will possibly make changes to line ordering based on observed levels of the shock parameter δ, i.e., $\lambda < \bar{\lambda} \equiv \int g^*(\delta)dF(\delta) - g^E$.

3.2 Testable Implications

We now turn to some analysis of comparative statics.

3.2.1 Output and Cost-of-effort Shocks

First, we elucidate the role of effort shocks in worker and supervisor decision-making.

Lemma 1. *Task-specific individual effort level is decreasing in δ.*

Proof. The claim to be proven is that e^*_{i1} and e^*_{i2} are decreasing in δ. Since the f.o.c.s must hold for all δ,

$$bh''e'_{i1} - c'' \cdot (e'_{11} + \gamma_i) = 0$$

implying

$$\frac{de^*_{i1}}{d\delta} = \frac{c''}{bh'' - c''}\gamma_i < 0$$

since c is convex and h is concave. Also,

$$b(g'_{21}e^*_{j1} + g_{22}e'_{i2}) - c''(e'_{i2} + \gamma_i) = 0$$

implying

$$\frac{de^*_{i2}}{d\delta} = \frac{c''\gamma_i - bg_{21}e'_{j1}}{bg_{22} - c''} < 0$$

since and c is convex, g is concave in both its elements, $g_{21} > 0$, and $e'_{j1} < 0$ as shown above. □

Using the above lemma, we can show that workers' output is decreasing in cost-of-effort shocks in all possible allocations of workers to tasks.

Proposition 1. *Order-specific output is decreasing in δ for both tasks.*

Proof. We show this for each task in turn.

Task 1: $\frac{dh(e_{i1}(\delta))}{d\delta} < 0$ for all δ.

This follows because $\frac{dh(e_{i1}(\delta))}{d\delta} = \frac{dh}{de_{i1}}\frac{de_{i1}}{d\delta} < 0$, since h is increasing in e, and e_{i1} is decreasing in δ by Lemma 1.

Task 2: $\frac{dg^1(\delta)}{d\delta} < 0$, $\frac{dg^2(\delta)}{d\delta} < 0$ for all δ.

$\frac{dg^1(\delta)}{d\delta} = g_1e'_{11} + g_2e'_{22} < 0$, $\quad \frac{dg^2(\delta)}{d\delta} = g_1e'_{21} + g_2e'_{12} < 0$ since g is increasing in all its inputs, and $e'_{ik} < 0$ for i=1,2 and k=1,2 by Lemma 1. □

As a corollary, line output will also be decreasing in the size of the cost-of-effort shock.

Corollary 1. *Observed line output is decreasing in δ.*

Proof. This corollary holds trivially, since line output is always either $g^1(\delta)$ or $g^2(\delta)$, and both of these are decreasing in δ from Proposition 1 above. □

Next, we study how task "difficulty" prompts differential impacts of cost-of-effort shocks on individual output. We embed task difficulty in the task-specific output functions. In particular, suppose each unit produced is scaled by $\beta \in (0,1)$ in the worker's maximization problems. That is, assume each actual unit of production "counts for" β units. The closer to 0 is β, the more "difficult" a task is said to be.[9]

To characterize the differential effects of more difficult tasks, we examine the responsiveness of worker output to cost-of-effort shocks, studying comparative statics in this responsiveness with respect to the difficulty parameter β. The following lemma establishes that optimal effort is increasing in difficulty of the task.

Lemma 2. *Worker effort is decreasing in task difficulty.*

Proof. We show that $\frac{\partial e_{i1}^*}{\partial \beta} > 0$, and omit the analogous proof of $\frac{\partial e_{i2}^*}{\partial \beta} > 0$ for brevity.

Recall that the necessary first-order condition for e_{i1} is $b\beta h'(e_{i1}^*) = c'(e_{i1}^* + \gamma_i \delta)$. Implicit differentiation with respect to β (and suppressing subscripts) yields

$$b(h'(e) + \beta h'' \frac{\partial e}{\partial \beta}) = c'' \frac{\partial e}{\partial \beta}. \tag{1}$$

Rearranging terms, we obtain

$$\frac{\partial e}{\partial \beta} = \frac{bh'}{c'' - \beta h'' b}. \tag{2}$$

The numerator of the above righthand-side expression is positive since $h' > 0$, and the denominator is also positive, since $c'' > 0$ and $h'' < 0$. Thus $\frac{\partial e_{i1}^*}{\partial \beta} > 0$, as we set out to show. $\square$

For what follows, we assume that $c''' \approx 0$, which would be the case, e.g., for any degree-two polynomial cost of the form $A_1 e^2 + A_2 e + A_3$. We then get the following proposition regarding the linkage between task difficulty and the responsiveness of output to cost-of-effort shocks.

Proposition 2. *The (negative) impact of cost-of-effort shocks on task-specific output is increasing in task difficulty.*

[9] This definition corresponds well to the industry-standard measure of "Standard Allowable Minutes," which captures (and standardize) the complexity of each task and garment.

Proof. We show that $\frac{\partial^2 e_{i1}^*}{\partial\delta\partial\beta} > 0$. Again, we omit an analogous proof of $\frac{\partial^2 e_{i2}^*}{\partial\delta\partial\beta} > 0$ for brevity.

We begin with implicit differentiation of the necessary first-order condition for e_{i1} with respect to δ. We obtain:

$$b\beta h''(e_{i1}^*)\frac{\partial e_{i1}^*}{\partial\delta} = c''(e_{i1}^* + \gamma_i\delta)(\frac{\partial e_{i1}^*}{\partial\delta} + \gamma_i). \tag{3}$$

Rearranging terms and suppressing subscripts, we get

$$\frac{\partial e}{\partial\delta} = \frac{c''\gamma}{b\beta h'' - c''} \tag{4}$$

Note that from above, $\frac{\partial e}{\partial\delta} < 0$ since $c'' > 0$ and $h'' < 0$.

Next, we obtain $\frac{\partial^2 e}{\partial\delta\partial\beta}$ by differentiating the above righthand-side expression with respect to β:

$$\frac{\partial^2 e}{\partial\delta\partial\beta} = \frac{\gamma c''' \frac{\partial e}{\partial\beta}\left(b\beta h'' - c''\right) - c''\gamma\left(b\left(h'' + \beta h''' \frac{\partial e}{\partial\beta}\right) - c''' \frac{\partial e}{\partial\beta}\right)}{\left(b\beta h'' - c''\right)^2}. \tag{5}$$

Since the sign of the above righthand-side expression only depends on the sign of the numerator (the denominator is always positive), we turn our focus to the numerator. This expression can be signed as follows:

$$\underbrace{\gamma c''' \frac{\partial e}{\partial\beta}\left(b\beta h'' - c''\right)}_{\approx 0} + \underbrace{-c''\gamma}_{<0}\left(b\underbrace{\left(h'' + \beta h''' \frac{\partial e}{\partial\beta}\right)}_{<0} + \underbrace{-c''' \frac{\partial e}{\partial\beta}}_{\approx 0}\right) > 0. \tag{6}$$

This proves that $\frac{\partial^2 e_1^*}{\partial\delta\partial\beta} > 0$, i.e., that the responsiveness of output to cost-of-effort shocks is increasing in task difficulty. □

3.2.2 Supervisor Behavior

Next, we consider supervisors' decisions to allocate workers to tasks and how they change with cost-of-effort shocks. In particular, we consider changes in the cost of effort occurring within an interval around 0 with the property that shifting the cost of effort from one side of the interval to the other changes the optimal allocation of workers to tasks. The following lemma shows the existence of this interval.

Lemma 3. *There exists* $(\underline{\delta}, \bar{\delta}) \in \mathbb{R}_- \times \mathbb{R}_+$ *such that*

$$\forall \delta \in (\underline{\delta}, 0), \quad g^2(\delta) < g^1(\delta)$$
$$\forall \delta \in (0, \bar{\delta}), \quad g^1(\delta) < g^2(\delta).$$

Proof. First note that if $\delta = 0$, $e^*_{11}(0) = e^*_{21}(0)$ and $e^*_{12}(0) = e^*_{22}(0)$. This implies $g^1(0) = g^2(0)$.

Claim: $g'^1(0) < g'^2(0)$.

Since $e^*_{11}(0) = e^*_{21}(0)$ and $e^*_{12}(0) = e^*_{22}(0)$, I can denote $g_1 \equiv g_1(e^*_{11}(0), e^*_{22}(0)) = g_1(e^*_{21}(0), e^*_{12}(0))$ and $g_2 \equiv g_2(e^*_{11}(0), e^*_{22}(0)) = g_2(e^*_{21}(0), e^*_{12}(0))$. Recall $g'^1(\delta) = \frac{dg^1(\delta)}{d\delta} = g_1 e'_{11} + g_2 e'_{22}$ and $g'^2(\delta) = \frac{dg^2(\delta)}{d\delta} = g_1 e'_{21} + g_2 e'_{12}$.

$$\begin{aligned}
& g'^1(0) - g'^2(0) \\
& \qquad = \quad g_1(e'_{11} - e'_{21}) + g_2(e'_{22} - e'_{12}) \\
& \qquad = \quad g_1(e'_{11} - e'_{21}) + g_2\left(\frac{c''\gamma_2 - bg_{21}e'_{11}}{bg_{22} - c''} - \frac{c''\gamma_1 - bg_{21}e'_{21}}{bg_{22} - c''}\right) \\
& \qquad = \quad \frac{c''}{bg_{22} - c''}(g_1(bg_{22} - c'') - bg_2 g_{21})\left(\frac{1}{bh'' - c''} - g_2\right)(\gamma_1 - \gamma_2) \qquad < \quad 0
\end{aligned}$$

Then since

(1) $g'^1(\delta) < 0$ and $g'^2(\delta) < 0$ for all δ,

(2) $g'^1(0) < g'^2(0) < 0$,

(3) $g^1(0) = g^2(0)$,

and g^1 and g^2 are continuous in δ, there exists a $\bar{\delta} > 0$ such that $g^2 > g^1$ for all $\delta \in (0, \bar{\delta})$. Similarly there exists a $\underline{\delta} < 0$ such that $g^2 < g^1$ for all $\delta \in (\underline{\delta}, 0)$. □

We consider implications for supervisor behavior of shifts between a "low" and a "high" level of cost of effort–namely, between $\delta_L \in (\underline{\delta}, 0)$ and $\delta_H \in (0, \bar{\delta})$, respectively. Examining this particular comparative static is of interest because it lets us study what happens when the cost of effort shifts enough that it changes the optimal worker-task ordering.

Table 1 categorizes the worker-task allocations of good and bad supervisors across these two levels of cost of effort. It makes clear that bad supervisors, because they choose not to invest in monitoring workers directly, do not switch worker ordering when the cost of effort shifts from δ_L to δ_H, keeping

	δ_L	δ_H
Bad supervisor ($\lambda > \bar{\lambda}$)	$g^1(\delta_L)$	$g^1(\delta_H)$
Good supervisor ($\lambda < \bar{\lambda}$)	$g^1(\delta_L)$	$g^2(\delta_H)$

Table 1: Worker-task allocations for good and bad supervisors across cost-of-effort shock levels

the ordering g^1 regardless of the level of cost of effort. On the other hand, good supervisors always invest in monitoring, and thus switch from g^1 to g^2 when the cost-of-effort shock parameter changes from δ_L to δ_H, because g^2 is optimal given $\delta = \delta_H$.

The following corollary follows directly from Table 1 and Lemma 3.

Corollary 2. *Bad supervisors ($\lambda > \bar{\lambda}$) always allocate workers to tasks following ordering g^1. For $\delta \in (\underline{\delta}, 0)$, good supervisors ($\lambda > \bar{\lambda}$) choose g^1, while for $\delta \in (0, \bar{\delta})$, they choose g^2.*

Proof. By definition, supervisors for whom $\lambda > \bar{\lambda}$ never invest in monitoring, and thus choose to allocate workers based on the expected output only, regardless of shock realizations. Thus, by the assumption $Eg^1 > Eg^2$, bad supervisors always choose g^1.

When $\lambda < \bar{\lambda}$, supervisors always invest in monitoring, and thus allocate workers to tasks based on realized levels of δ. By Lemma 3, the optimal allocation of workers to tasks follows g^1 when $\delta \in (\underline{\delta}, 0)$, but follows g^2 when $\delta \in (0, \bar{\delta})$. □

Note that this corollary implies that increasing the cost-of-effort shock parameter (from δ_L to δ_H) will induce good supervisors to switch line ordering, and decreasing this parameter (from δ_H to δ_L) will induce switching for good supervisors, as well.

Next we study the repercussions of differential worker allocation by good and bad supervisors on line output.

Proposition 3. *Good supervisors have higher expected line output than bad supervisors on the interval $(\underline{\delta}, \bar{\delta})$.*

Proof. We know that for $\delta \in (0, \bar{\delta})$, $g^2(\delta) > g^1(\delta)$. Thus,

$$\int_{\underline{\delta}}^{\bar{\delta}} g^1(\delta) dF(\delta) \quad < \quad \int_{\underline{\delta}}^{0} g^1(\delta) dF(\delta) + \int_{0}^{\bar{\delta}} g^2(\delta) dF(\delta). \tag{7}$$

This proves the proposition. □

Finally, we examine the extent to which good supervisors are able to mitigate fluctuations in output occurring because of shifts in the cost-of-effort shock parameter.

Proposition 4. *Consider an increase in δ from $\delta_L \in (\underline{\delta}, 0)$ to $\delta_H \in (0, \bar{\delta})$. Both good and bad supervisors experience decreases in output as a result of this increase in δ, but the reduction in output is smaller for good supervisors.*

Proof. Consider the change in output resulting from increasing δ from δ_L to δ_H:

$$\text{Bad supervisors:} \qquad g^1(\delta_H) - g^1(\delta_L) \tag{8}$$

$$\text{Good supervisors:} \qquad g^2(\delta_H) - g^1(\delta_L). \tag{9}$$

For bad supervisors, it is clear that $g^1(\delta_H) - g^1(\delta_L) < 0$, since g^1 is decreasing in δ.

For good supervisors, note that $g^2(\delta_H) < g^2(\delta_L)$ since g^2 is decreasing in δ. Then, it follows that $g^2(\delta_H) - g^1(\delta_L) < g^2(\delta_L) - g^1(\delta_L) < 0$. Thus output decreases for both good and bad supervisors when the cost-of-effort shock rises from δ_L to δ_H. But note that since $g^2(\delta_H) > g^1(\delta_H)$ by Lemma 3, the change in output will be less negative for good supervisors. This proves what we set out to show. □

Finally, we discuss the way in which switching worker ordering delivers bottleneck relief. Specifically, we decompose the effect of a change in line order on total output into 1) a direct effect of switching workers to different tasks, and 2) so-called bottleneck relief. The direct effect of workers on individual tasks result from the workers' differential costs of effort (sensitivity to cost-of-effort parameter), and the indirect effects result from the complementarity of the workers' effort levels, which can create bottleneck effects.

To see this more clearly, consider the change in final output when changing the line order from g^2 to g^1. At this point we introduce some new notation. Given δ, let $e^*_{ij} \equiv e^*_{ij}(\delta)$, where i denotes worker and j denotes task, and let $e_{i2}(e)$ denote worker i's optimal effort level for task 2, when e is the effort level of the worker assigned to task 1. Then for a given δ, the difference in production when switching from g^2 to g^1 can be written as

$$g(e^*_{11}(\delta), e^*_{22}(\delta)) - g(e^*_{21}(\delta), e^*_{12}(\delta))$$

$$= \underbrace{g(e^*_{21}, e_{22}(e^*_{21})) - g(e^*_{21}, e^*_{12})}_{\text{worker effect on task 2}} + \underbrace{g(e^*_{11}, e_{22}(e^*_{21})) - g(e^*_{21}, e_{22}(e^*_{21}))}_{\text{worker effect on task 1}}$$

$$+ \underbrace{g(e^*_{11}, e^*_{22})) - g(e^*_{11}, e_{22}(e^*_{21}))}_{\text{bottleneck relief}} \tag{10}$$

The first component, labeled "worker effect on task 2", denotes the change in output that would occur if worker 2 was assigned to task 2 instead of worker 1, while the quantity of input q_1 remains unchanged. Thus it measures the individual effectiveness of worker 2 over worker 1 when matched with task 2, holding all else equal.

The second component, labeled "worker effect on task 1", measures the change in output that stems from switching in worker 1 for worker 2 at task 1, holding the effort level exerted to task 2 constant at the level described above. Thus this component measures the individual effectiveness of worker 1 over worker 2 when matched with task 1, holding all else equal.

The third component, labeled "bottleneck relief", measures the increase in output that stems from effort complementarity between the two tasks. It measures the output effect via the increase in effort provided by worker 2 at task 2, as an optimal response to an increase in input 1 in the production of the final good. In this sense, this effect can be interpreted as a bottleneck effect because, a low output in the first task would induce a low level of effort by the worker assigned to task 2, hence creating a "bottleneck" in the production process.

3.3 Summary of Predictions

Our model studies the effects of cost-of-effort shocks on worker productivity, and lays out one mechanism through which good managers are able to blunt the impact of these shocks. In our model, good supervisors are those who invest in closely monitoring their workers, and change the allocation of workers to tasks on a production line in response to effort shocks. Optimal allocation varies with this shock because workers experience the shock differently. As a result, good supervisors mitigate the impacts of shocks on productivity by re-optimizing this allocation.

Below, we summarize each of the predictions discussed in the model, translating them into our empirical context and reordering slightly to better fit the progression of the content that follows.

1. Good supervisors have higher line output on average than bad supervisors (Proposition 3).
2. Good supervisors monitor their workers and thus are more likely to make changes to line ordering; bad supervisors monitor less and thus are less likely to change line ordering (Corollary 2).
3. Worker and line output are decreasing in pollution (Proposition 1 and Corollary 1).
4. The impact of pollution on worker output is increasing task difficulty (Proposition 2).
5. Switching line ordering increases line output due to direct effects of differential effectivenesses of task-matching and indirect effects stemming from relieving bottlenecks (Equation 10).
6. Good supervisors experience smaller decreases in line output than bad supervisors as a result of pollution shocks (Proposition 4).
7. Large enough changes in pollution shift the optimal line ordering (Lemma 3).
8. Good supervisors make switches to line ordering in response to both increases and decreases in pollution levels. Bad supervisors are less likely to switch line ordering in response to pollution levels (Corollary 2).

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.[10] 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. We average across monitors within floor, for two reasons: 1) within floor correlation across monitors is very high, and 2) some observations are missing for some monitors for some hours on some days

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

(most likely due to power continuity issues). Taking within floor averages for hourly observations maximizes the number of non-missing observations without substantial loss to identifying variation in the pollution measures.

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 particulate matter (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 produced by the garment production process and could therefore exhibit reverse causality: high efficiency produces high coarse PM levels. Lastly, as previously discussed, 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.[11]

Figure 1A

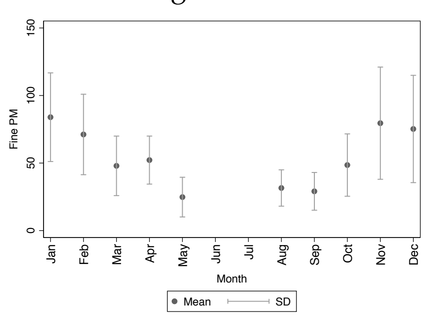


Figure 1B

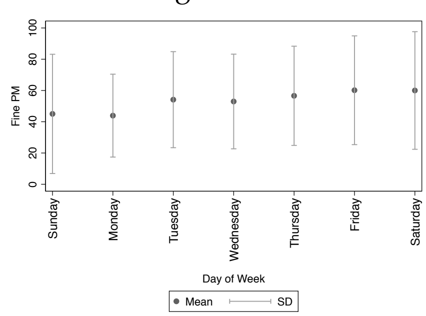
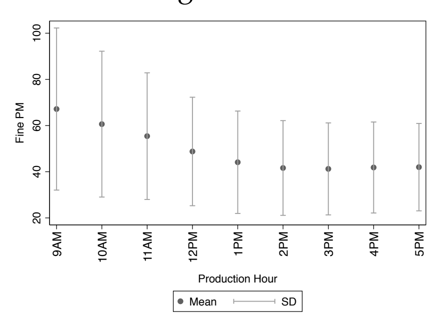


Figure 1C



Figures 1A-1C depict means and standard deviations of fine particulate matter within each month, day of the week, and hour of the day, respectively. Note that June and July do not appear in our dataset; Sundays are non-production days; and production hours are between 9am and 5pm.

[11]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.

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 beginning 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. The PM data used in this study are from August 2013 through early May 2014.

4.2 Production Data

Production data were 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. These inputs were then transmitted directly into the firms administrative data servers via wireless network connection.

4.2.1 Productivity

The key measures of worker and line productivity we study below are pieces produced and efficiency. At the worker-hour level, pieces produced are simply the number of garments that passed a worker's station by the end of that production hour. For example, if the worker's operation were to sew 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." In order to calculate line-level hourly production from these worker-hour observations, we average the pieces produced by 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.

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. That is, a garment style with a SAM of .5 is deemed to take a half minute to produce one complete garment.[12] SAM, as the name denotes, is standardized across the global garment industry and is drawn from an industrial

[12] A SAM of .5 is not unlikely. The mean of SAM across worker hourly observations is .61 and its standard deviation is .20.

engineering database. However, this measure may 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 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 $60/.5 = 120$.

Figure 2A

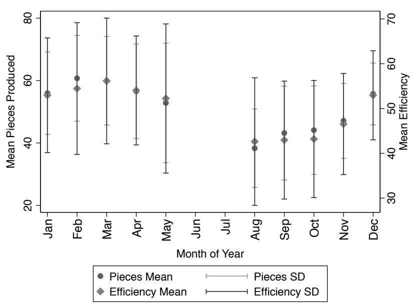


Figure 2B

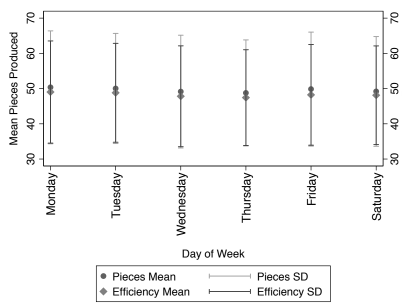
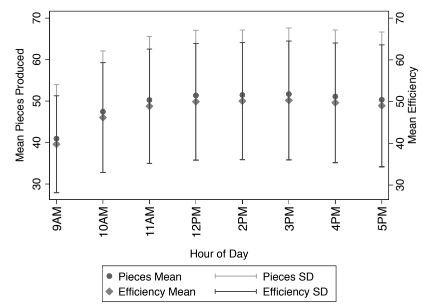


Figure 2C



Figures 2A-2C depict means and standard deviations of efficiency (left y-axis) and pieces produced (right y-axis) within each month, day of the week, and hour of the day, respectively. Note that June and July do not appear in our dataset; Sundays are non-production days; and production hours are between 9am and 5pm.

As shown in Figures 2A-2C, productivity also follows mild seasonal and hour-of-day patterns. Specifically, productivity peaks around March with late winter and early spring showing high productivity, as well. These patterns line up with the seasonal global demand in the ready-made garments industry. Productivity trends upwards through the first 3-4 hours of the day before plateauing.

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

4.2.2 Task Match Adjustments

The other main outcome measure we use in the empirical analysis is a dummy for any task match adjustment on the line. Specifically, we first define "task match adjustment" 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 match adjustment dummy variable as a 1, and code a 0 if they are doing the same operation as in the last hour. We ignore operation changes across days and reassignment of workers across lines as these are primarily driven by manpower fluctuations rather than worker-specific productivity issues.

We then construct the line-level task match adjustment measure we use in the analysis from these worker-hour task match adjustment measures. *Any Task Match Adjustment* 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 match adjustment measure discussed above.

4.3 Management Survey Data

In order to assess managerial quality, we surveyed production line supervisors in the factory, measuring demographic characteristics, managerial practices, managerial skills, and personality traits. We drew from several sources to construct the management questionnaire, in particular borrowing heavily from Bloom and Van Reenen (2010) to construct instruments measuring management practices, skills, and styles. We assemble two indices out of five variables that most closely measure the notion of managerial quality and effort discussed in section 3 above.

The *Production Problem Solving Index* is constructed from three variables: 1) a dummy variable for whether the line supervisor reports that he generally learns about production issues from talking to workers on the line, 2) a dummy variable for whether the line supervisor is fluent in the native language of the majority of the workers on the line, and 3) a dummy variable for whether the supervisor reports generally solving production issues on his own without having to consult others. 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 dummies are then averaged across all supervisors assigned to the line, and the index is a simple sum of these three averaged dummies, taking values of 0 to 3. This index is meant to measure in a general sense the degree to which the manager is able to detect and solve production issues.

The *Monitoring and Reallocation Index* is constructed from two variables: 1) a dummy variable for whether the supervisor reported making rounds of the line to monitor production at least every 10 min (which was the highest possible frequency response) , and 2) a dummy variable for whether the supervisor reported that they would try to replace a worker that was performing poorly. In translating these variables to the line level, we construct a dummy for whether *all* supervisors of a line reported monitoring at least every 10 minutes, and calculate the average across supervisors of a line for the worker replacement variable as a measure of the probability that an underperforming worker is replaced. The index is then a simple sum of these two variables, taking values of 0 to 2, and is meant to measure the degree to which managers engage in the specific activities modeled as evidence of higher effort or quality in section 3 above. Lastly, we construct a *Composite Index* which is simply the sum of the *Production Problem Solving Index* and the *Monitoring and Reallocation Index*, taking values 0 to 5.

Finally, we also utilize variables measuring specific managerial practices, management style, and personality traits in descriptive regressions aimed at unpacking the information contained in the indices discussed above. For managerial practices, we focus on which specific activities the supervisor reports engaging in to ensure that production targets are met. These include making rounds of the line and discussing targets with workers among other activities. We construct a mean effect measure from individual binary variables for each of these activities. We construct analogous mean effect measures for activities related to reinforcing high level performance from star workers (e.g., acknowledging high performance in front of other workers, recommending star performers for promotions) and for activities related to retaining high performing workers (e.g., talk to worker directly to convince them to stay, recommend a salary increase). For management style, we construct two analogous mean effect measures: 1) positive leadership behavior (e.g., give advance notice of changes, back up the workers on line, explain my actions); and 2) passive conflict resolution (e.g., direct reports resisted initiatives, had interpersonal conflicts with direct reports). We also construct four mean effects measures from standard psychological modules on personality: in particular, conscientiousness, locus of control, perseverance, and self-esteem. Further detail regarding these measures is given in the Data Appendix.

4.4 Summary Statistics

Table 2 presents summary statistics of the main variables of interest. Fine PM in the pooled sample is roughly 51, with a standard deviation of roughly 26. The units of fine PM have been translated as closely as possible to $\mu g/m^3$ in order to allow for easy comparison with impacts from previous studies.[13] Pieces produced and efficiency both have means of roughly 50. Task Match Adjustment

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

Table 2: Summary Statistics

	(1) Worker-Hour Sample		(2) Line-Hour Sample		(3) Supervisor Line-Hour Sample	
Number of observations	1,054,962		14,342		11,974	
Number of days	210		210		210	
Number of workers	1750		-		-	
Number of lines	17		17		13	
Number of Line Supervisors	-		-		24	
	Mean	SD	Mean	SD	Mean	SD
Pollution						
Fine PM	51.47597	26.52471	51.32857	26.11829	51.31172	26.05516
Coarse PM	624.1194	217.1332	622.1406	214.5416	611.5284	209.0065
Production						
Pieces Produced	50.59853	22.39275	49.56163	15.76222	50.37713	16.44089
Hourly Efficiency	49.14378	21.12376	48.22987	14.1346	48.81886	14.53656
Task Match Adjustment						
Any Task Match Adjustment			0.4181425	0.493271	0.4154	0.4928115
Pct of Workers Reallocated			1.235551	2.07021	1.194546	2.01871
Managerial Quality Indices						
Production Problem Solving Index					2.067841	0.9381541
Monitoring and Reallocation Index					1.567326	0.391975
Composite Index					3.635168	1.152347

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. Production Problem Solving Index is constructed from three variables: 1) a dummy variable for whether the line supervisor reports that he generally learns about production issues from talking to workers on the line, 2) a dummy variable for whether the line supervisor is fluent in the native language of the majority of the workers on the line, and 3) a dummy variable for whether the supervisor reports generally solving production issues on his own without having to consult others. 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 dummies are then averaged across all supervisors assigned to the line, and the index is a simple sum of these three averaged dummies, taking values of 0 to 3. This index is meant to measure in a general sense the degree to which the manager is able to detect and solve production issues. Monitoring and Reallocation Index is constructed from two variables: 1) a dummy variable for whether the supervisor reported making rounds of the line to monitor production at least every 10 min (which was the highest possible frequency response) , and 2) a dummy variable for whether the supervisor reported that they would try to replace a worker that was performing poorly. We take the minimum value across the supervisors of the line for the monitoring dummy since the majority of supervisors reported monitoring every 10 min. We do this to maximize the amount of variation in this variable. We average the second dummy as responses were more balanced to this question. The index is a simple sum of these two variables, taking values of 0 to 2, and is meant to measure the degree to which managers engage in the specific activities modeled as products of higher effort or quality in the model. Composite Index is simply the sum of the Production Problem Solving Index and the Monitoring and Reallocation Index, taking values 0 to 5.

is quite common, with over 40% of line-hour observations reporting at least one worker reassigned. However, a small percentage of workers on the line are reassigned on average: only 1.2% of workers on the line are reassigned, or less than 3% conditional on any task match adjustment. With an average of just under 82 workers per line in a given hour, the average line thus sees about 2.5 workers reallocated per hour.

5 Empirical Strategy

5.1 Overview

The empirical analysis proceeds in several steps, following the model summary in section 3. We first estimate the degree to which average line productivity varies by managerial quality. We do this by regressing line productivity measures on the different managerial indices we have constructed, along with an appropriate set of controls to account for the coincident patterns over time in pollution and productivity discussed in section 4. We later estimate the degree to which average task match adjustment on the line varies by managerial quality in much the same way.

Next, we estimate the impact of pollution (fine PM) on both worker and line level productivity measures, controlling for contemporaneous coarse PM levels and month, day-of-week, and hour-of-day fixed effects. We then estimate the degree to which this impact varies by task difficulty (as measured by SAM), and by position in the line (the so-called "seat in line"). These heterogenous impacts of pollution on worker-task productivity are also predicted by the model and, if verified empirically, would help to validate the appropriateness of the model for our empirical context. Most importantly, we estimate the degree to which the impact of pollution varies by managerial quality.

Finally, we estimate the reallocation response to pollution exposure (or more specifically, deviations from "usual" pollution levels) and the degree to which these responses vary by managerial quality. We conclude by estimating partial correlations between managerial quality and specific practices, style, and personality traits in order to unpack the determinants of our indices.

5.2 Specifications

We estimate the following managerial quality specification for productivity of line l in hour h on day of the week d in month m and year y:

$$P_{lhdmy} = \alpha_0 + \zeta M_l + \beta FPM_{fhdmy} + \phi CPM_{fhdmy} + \psi_y + \gamma_h + \eta_m + \delta_d + \varepsilon_{lhdmy} \tag{11}$$

Here, ζ is the coefficient of interest, measuring the relationship between managerial quality and line productivity. As discussed in section 4, M_l represents one of 3 managerial indices: Production Problem Solving Index, Monitoring and Reallocation Index, and Composite Index. Also as discussed in section 4, we use both pieces produced and efficiency as measures of line level productivity. FPM is fine PM and CPM is coarse PM on floor f for hour h on day d in month m and year y.[14] γ_h are hour fixed effects; ψ_y are year fixed effects; η_m are month fixed effects; and δ_d are day-of-week fixed effects. ε_{lhdmy} is an error term.[15] In all specifications with pieces produced as the outcome, we include target pieces as an additional control. We do not need this control when using efficiency as the outcome, since target pieces is already in the denominator of efficiency. This control accounts for variation in productivity due to the complexity of the garment.

We include this control in specifications of pieces produced below as well. We then estimate specifications in which we replace productivity outcomes P_{lhdmy} with the task match adjustment outcome R_{lhdmy}. When doing so we replace linear pollution controls FPM and CPM with above and below-median linear splines to account for the non-monotonic relationship between pollution and task match adjustment predicted by the theory.

We estimate the following pollution specification for the productivity of worker i in hour h on day

[14]Although we collected simultaneous pollution measurements from 5 monitors across the 2 production floors (i.e., 3 on one floor and 2 on the other), some measurements are missing for some hours on some days. The measurements are also very highly correlated within floor. Accordingly, we average across non-missing measurements for each floor to minimize the number of missing values. We have run results using both raw individual measurements from each monitor and averaging across both floors and find qualitatively identical results.

[15]Although we believe these errors to be close to i.i.d across worker-hour observations after conditioning on the full set of time fixed effects, we want to be conservative in allowing for errors to be correlated within production line given that in these basic specifications the regressor of interest varies at only the production line level. Accordingly, we report line-specific random effect robust errors as our main standard errors in estimates from this specification to allow for errors to be equicorrelated within line. In all more complex specifications below in which pollution measures and interactions with pollution are our main regressors of interest, we report errors clustered at the hour by date level since these regressors vary at that level. We, however, report additional more conservative estimated standard errors in appendix tables to demonstrate additional robusntess, but believe these models to be less appropriate for our empirical context.

of the week d in month m and year y:

$$P_{ihdmy} = \alpha_0 + \beta FPM_{fhdmy} + \phi CPM_{fhdmy} + \psi_y + \gamma_h + \eta_m + \delta_d + \varepsilon_{ihdmy} \tag{12}$$

Here, β is the main coefficient of interest, measuring the impact of exposure to fine particulate matter level, FPM, on floor f for hour h on day d in month m on worker hourly productivity P. Error ε_{ihdmy} is assumed i.i.d. conditional on hour of the day x date. That is, errors are clustered at the hour by date level. This is the appropriate level of clustering given that the regressor of interest (fine PM) varies at the hour by date level. We estimate equation 12 at the line level as well, as the model predicts impacts of pollution on both worker and line level productivity. CPM is coarse PM on floor f for hour h on day d in month m. γ_h are hour fixed effects; ψ_y are year fixed effects; η_m are month fixed effects; and δ_d are day-of-week fixed effects.

In additional specifications, we also include line fixed effects α_l. Later, we once again estimate specifications in which we replace P_{lhdmy} with the reallocation outcome R_{lhdmy} and linear pollution regressors FPM and CPM with above and below median splines as well as symmetric (absolute value) deviations from the median. We also estimate specifications similar to that in equation 12, but with, alternately, additional main effect regressors for our "task difficulty" measure (SAM) and our "seat in line" measure along with their interactions with pollution measures. These are meant to empirically test the additional implications of the model regarding heterogeneity in the impacts of pollution on productivity.

In the next specification, we include interactions between managerial quality indices and pollution levels. This specification estimates the degree to which the impact of fine PM on productivity differs by managerial quality. Specifically, we estimate the following amended specification:

$$\begin{aligned} P_{lhdmy} = \alpha_0 + \lambda_f(FPM_{fhdmy} \times M_l) + \lambda_c(CPM_{fhdmy} \times M_l) + \zeta_l + \beta FPM_{fhdmy} + \phi CPM_{fhdmy} \\ + \psi_y + \gamma_h + \eta_m + \delta_d + T_{dmy} + \varepsilon_{lhdmy} \end{aligned} \tag{13}$$

Here, λ_f is the coefficient of interest. Note we add line level fixed effects, ζ_l, here for additional rigor and thus omit the main effects of managerial quality as these are absorbed by the line fixed effects. Once again, we assume errors ε_{ihdmy} are clustered at the hour by date level. Although, we believe this is the appropriate error structure to impose, we explore robustness to relaxing this assumption to allow for two types of within-line correlation in the errors in Tables A3 and A4 of the Appendix. Next, to explore the mechanisms driving these heterogeneous productivity impacts of pollution by managerial quality, we also re-estimate equation 13 replacing outcome P_{lhdmy} with R_{lhdmy} and pollution measures FPM and CPM with, alternately, above and below median splines and symmetric (absolute value) deviations from the median in both the main effect and interaction terms.

Finally, we validate the managerial quality index results by reestimating the reallocation version of equation 13 but with the addition of a supervisor residual TFP measure as an alternate measure of managerial quality; and then attempt to decompose managerial quality into specific practices, style, and personality measures. We do this by first estimating a worker level log production function (i.e., ln(pieces produced) on time fixed effects from the main specification and worker fixed effects to account for individual worker contributions to output) and constructing average line level predicted residual measures. These line averaged predicted residuals reflect, among perhaps other determinants, supervisor contributions to output; we, accordingly, call these supervisor residual TFP measures.[16]

We construct a dummy for above median supervisor TFP residual from these measures and estimate specifications similar to equation 13 with R_{lhdmy} as the outcome, spline and absolute deviation from median pollution regressors, and additional terms for the interaction of above median supervisor residual TFP with the pollution measures.[17] We then regress the constructed supervisor residual TFP measure on the managerial quality indices to investigate their partial correlations. We finish by regressing each of the managerial quality indices and the constructed supervisor residual TFP measure on additional measures from the management survey we conducted. These additional measures reflect specific management practices, management style, and personality traits and help to decompose the information contained in the managerial indices used in the main regressions.

[16]Note that this specification matches a log-linearized Cobb-Douglas production function with each worker as an input and the regression coefficient on them as the marginal productivity i.e. the production function is given by $Y = A_t(L_1^{b_1}...L_k^{b_k})$, with $A_t = e^{(c_s D_s + a_t D_t)}$, where D_s is the supervisor's contribution to production, c_s is the factor load on the supervisor's contribution, D_t are the time dummy variables, and c_t is the vector of factor loads on the time dummy variables. The log-linear version of this production function is thus given by $ln(Y) = \gamma_h + \psi_y + \eta_m + \delta_d + \kappa_w + \epsilon$, where $\gamma_h, \psi_y, \eta_m,$ and δ_d are time fixed effects (hour of the day, year, month, and day of the week fixed effects, respectively), κ_w are worker fixed effects, and the mean of the residual ϵ at the line level is the supervisor contribution to production c_s (the supervisor TFP residual measure). It should be made clear that the outcome in this regression (i.e., ln(pieces produced)) differs from our usual outcome (i.e., pieces produced in levels) because the previous regressions are meant to provide results of reduced form tests of implications from the model in which we did not impose any particular functional form (unlike the Cobb-Douglas form imposed here to recover production function residual TFP of the supervisor). This strategy is similar to Bloom et al. (2012) in that the objective is to compare how management measures are related to the TFP residual, but the procedure itself is most similar to that of Stolarick et al. (1999), since that is the most appropriate way to map productivity net of other factors to supervisors in our setting.

[17]Note main effects of supervisor residual TFP is absorbed by line fixed effects.

Table 3: Managerial Quality and Line Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Pieces Produced mean(pieces produced by workers on line within hour)			Efficiency mean(pieces produced / target pieces)		
Production Problem Solving Index	3.15390***			3.04921***		
	(0.12960)			(0.12109)		
Monitoring and Reallocation Index		2.83950***			2.91093***	
		(0.30630)			(0.29667)	
Composite Index			2.33202***			2.30863***
			(0.10347)			(0.09787)
Production Target		Control Regressor			Outcome Denominator	
Fine and Coarse PM Controls			Linear			
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,974	11,974	11,974	11,974	11,974	11,974
Mean of Dependent Variable		50.38			48.82	

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). The errors reported are random effects errors which allow for equicorrelated errors within line.

6 Results

6.1 Managerial Quality and Production

We begin in Table 3 by presenting results from the estimation of equation 11. Estimates correspond to coefficient(s) of interest ζ in equation 11. As described in the theory, lines managed by supervisors of higher managerial quality should achieve higher expected line output. Indeed, we find across all specifications that higher managerial quality as measured by each of the managerial indices predicts higher productivity, both in terms of mean pieces produced by workers on the line in an hour and mean efficiency. Specifically, we find that a one unit increase in each of the indices leads to a higher expected output of roughly between 2.3 and 3.2 pieces produced per hour or between 2.3 and 3 percentage points in efficiency. These coefficients represent an increase of around 6% of the means of these productivity outcomes for each 1 unit change in these indices. As shown in Table 2, a one unit change is roughly a standard deviation of both the *Production Problem Solving Index* and *Composite Index* and roughly 2.5 standard deviations in the *Monitoring and Reallocation Index*.

6.2 Managerial Quality and Task Reallocation

Next, we estimate equation 11 with task match adjustment as the outcome (and pollution controls adjusted appropriately). These estimates are reported in Table 4 and once again validate the model

Table 4: Managerial Quality and Task Match Adjustments

	(1)	(2)	(3)
		Any Task Match Adjustment 1(at least one worker on line reassigned to a different task this hour from last hour)	
Production Problem Solving Index	0.01256** (0.00483)		
Monitoring and Reallocation Index		0.14737*** (0.01148)	
Composite Index			0.02497*** (0.00389)
Fine and Coarse PM Controls		Above and Below Median Absolute Value Deviation Splines	
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes
Observations	11,974	11,974	11,974
Mean of Dependent Variable		0.42	

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). The errors reported are random effects errors which allow for equicorrelated errors within line.

prediction that lines supervised by higher quality managers are more likely to engage in task match adjustment. Specifically, a one unit increase in the *Monitoring and Reallocation Index* leads to a roughly 15 percentage point rise in the probability of any task match adjustment. We also find that the *Production Problem Solving Index* has a small but significant impact on task reallocation outcomes. Naturally, by construction, we expect the *Monitoring and Reallocation Index* to most strongly predict task match adjustment, but expect the better problem identification and problem solving behaviors embodied in the *Production Problem Solving Index* to correlate with reallocation as well. This seems borne out quite robustly in the data.

6.3 Impacts of Pollution on Worker and Line Productivity

Next, we validate the assertion in the theory that exposure to fine particulate matter pollution represents a negative productivity shock at both the worker and line level in our empirical context. We start by graphically depicting the relationships between productivity variables and fine particulate matter pollution exposure (controlling for coarse PM exposure, time FE and line FE). These graphs are pre-

Figure 3A

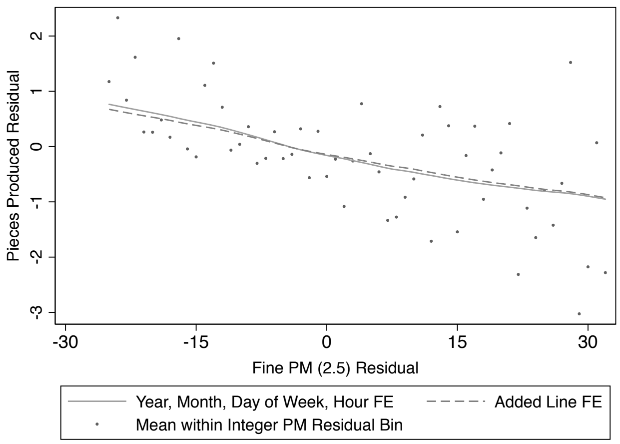
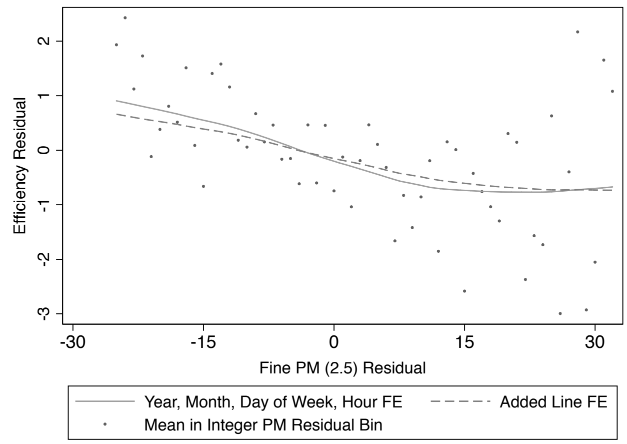


Figure 3B



Figures 3A and 3B depict relationships between residuals of fine PM exposure and pieces produced (3A) or efficiency (3B). 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 residual trimmed at 5th and 95th percentile. Scatter depicts mean residual of productivity measure within integer fine PM residual bins, Lines depict local polynomial smoothing with and without production line fixed effects included in regression producing residuals.

sented in Figures 3A (pieces produced) and 3B (efficiency) and show clear negative relationships of roughly linear form. Note these graphs depict relationships in line level data, but very similar pictures are obtained using worker level data.

Next, we report analogous regressions results from the estimation of equation 12 at the worker level in Table 5 and analogous line level productivity impacts in Table 6. The estimates in both Tables 5 and 6 show large, negative, and statistically significant impacts of fine PM exposure on both pieces produced and efficiency. Specifically, we find that a one standard deviation increase in fine PM levels leads to a reduction of roughly .7 garments at the worker level each hour and more than half a garment per hour on average at the line level. In terms of efficiency, we find a reduction of .67 percentage points efficiency for workers and between .53 and .62 percentage points on average for the line.

Table 5 also includes results from regressions testing the predictions of the model regarding heterogeneity of pollution impacts by task difficulty (SAM) and seat in line.[18] Specifically, the model predicts that the more difficult the task the *larger* the loss in productivity. This result is consistent with the physiological convexity of pollution impacts shown in laboratory studies as well. Indeed, we find strong evidence of this prediction in column 2. Note we cannot run the analogous interaction regression for

[18] We normalize the SAM variable by subtracting its mean and dividing by its standard deviation to improve interpretability.

Table 5: Pollution and Worker Productivity

	(1)	(2)	(3)	(4)	(5)
	Pieces Produced pieces produced by worker this hour			Efficiency (pieces produced / target pieces)	
Fine PM (Std)	-0.69843***	-0.72892***	-0.19781	-0.66694***	-0.22024
	(0.17564)	(0.17309)	(0.19612)	(0.16508)	(0.19072)
Task Difficulty (SAM Std) X Fine PM (Std)		-0.28229***			
		(0.07371)			
Seat in Line X Fine PM (Std)			-0.01135***		-0.01021***
			(0.00167)		(0.00160)
Production Target		Control Regressor		Outcome Denominator	
Coarse PM and Interaction Controls			Linear		
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	No	Yes
Observations	1,054,962	1,054,962	1,054,962	1,054,962	1,054,962
Mean of Dependent Variable		50.60		49.14	

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the date-hour level. See Table A2 for robustness to the inclusion of additional weather controls.

Table 6: Pollution and Line Productivity

	(1)	(2)	(3)	(4)
	Pieces Produced mean(pieces produced by workers on line within hour)		Efficiency mean(pieces produced / target pieces)	
Fine PM (Std)	-0.54986***	-0.52778***	-0.61537***	-0.53065***
	(0.18618)	(0.18599)	(0.18063)	(0.17713)
Production Target	Control Regressor		Outcome Denominator	
Coarse PM Controls		Linear		
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Line FE	No	Yes	No	Yes
Observations	14,342	14,342	14,342	14,342
Mean of Dependent Variable	49.56		48.23	

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

the efficiency outcome as SAM is in the denominator of the formula for efficiency.[19] The model also predicts that due to bottlenecks arising from sequential complementarities between workers in the line, workers further down the line will have larger impacts of pollution with total impacts coming from both direct impacts on their productivity and indirect impacts coming from lost productivity of workers earlier in the line. Indeed, we find in both columns 3 and 5 that the impacts of pollution on productivity are more negative for workers further down the production line.

6.4 Impacts of Pollution on Line Productivity by Managerial Quality

Figure 4A

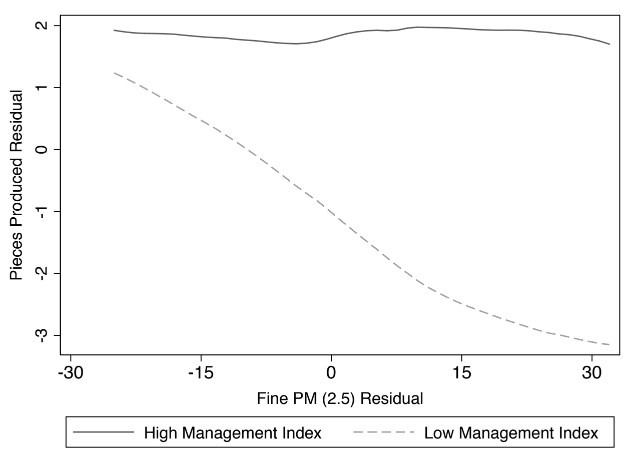
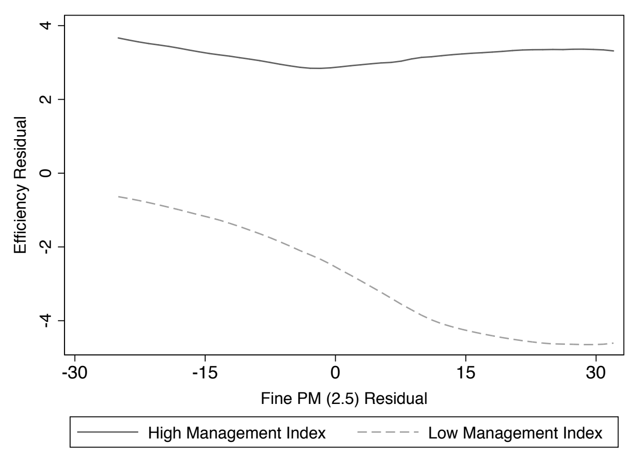


Figure 4B



Figures 4A and 4B depict relationships between residuals of fine PM exposure and pieces produced (4A) or efficiency (4B) by high and low managerial quality. High management corresponds to above median Composite Index; low management to below median. 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 residual trimmed at 5th and 95th percentile. Lines depict local polynomial smoothing.

Having established relationships between managerial quality and productivity and between pollution and productivity, we next test the theoretical claim that lines supervised by higher quality managers will suffer smaller losses in productivity due to pollution exposure. Note that the model predicts that this relationship will be monotonic, such that increases in pollution will reduce the productivity of lines supervised by higher quality managers less than that of lines of lower quality managers and decreases in pollution will increase the productivity of lines of higher quality managers more than it will for lines of lower quality managers. Accordingly, we estimate the linear interaction specification

[19] That is, efficiency is pieces produced over target pieces, where target pieces is 60 over SAM.

Table 7: Pollution and Line Productivity by Managerial Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	Pieces Produced mean(pieces produced by workers on line within hour)			Efficiency mean(pieces produced / target pieces)		
Production Problem Solving Index X Fine PM	0.48718***			0.52112***		
	(0.12794)			(0.13269)		
Monitoring and Reallocation Index X Fine PM		1.09919***			1.09415***	
		(0.31340)			(0.30370)	
Composite Index X Fine PM			0.45384***			0.47403***
			(0.10835)			(0.11144)
Fine PM	-2.04335***	-2.66716***	-2.65341***	-2.05369***	-2.60206***	-2.66560***
	(0.40296)	(0.55562)	(0.51522)	(0.40984)	(0.54156)	(0.52416)
Production Target		Control Regressor			Outcome Denominator	
Coarse PM and Interaction Controls			Linear			
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,974	11,974	11,974	11,974	11,974	11,974
Mean of Dependent Variable		50.38			48.82	

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the date-hour level. See Table A3 for robustness to within-line correlation in errors.

described in equation 13. This functional form decision is validated by the graphical representation of these interaction effects depicted in Figures 4A and 4B, which show that lines of managers with above median *Composite Index* values have roughly flat productivity-pollution gradients, while lines of managers with below median *Composite Index* values have starkly negative gradients for both productivity measures. The analogous regression results from the estimation of equation 13 reported in Table 7 verify these patterns. Specifically, we find that a one unit increase in one of the managerial quality indices offsets roughly 1/5 to over 1/3 of the impact of pollution on the lowest quality managers (i.e., those with managerial index value of 0). When scaled by the possible range of values for each index, we find that the highest quality managers suffer losses roughly 75 to nearly 100% smaller than do the lowest quality managers.

6.5 Task Match Adjustment in Response to Pollution

Next, we empirically establish task reallocation as a primary mechanism by which the attenuation in pollution impacts on productivity for higher quality managers shown in Table 7 is achieved. We start by estimating equation 12 with task match adjustment as the outcome and more general functional forms of the pollution measure as the regressors of interest. Specifically, note that the model predicts that task reallocation responses to pollution fluctuations will not be monotonic like the im-

Figure 5

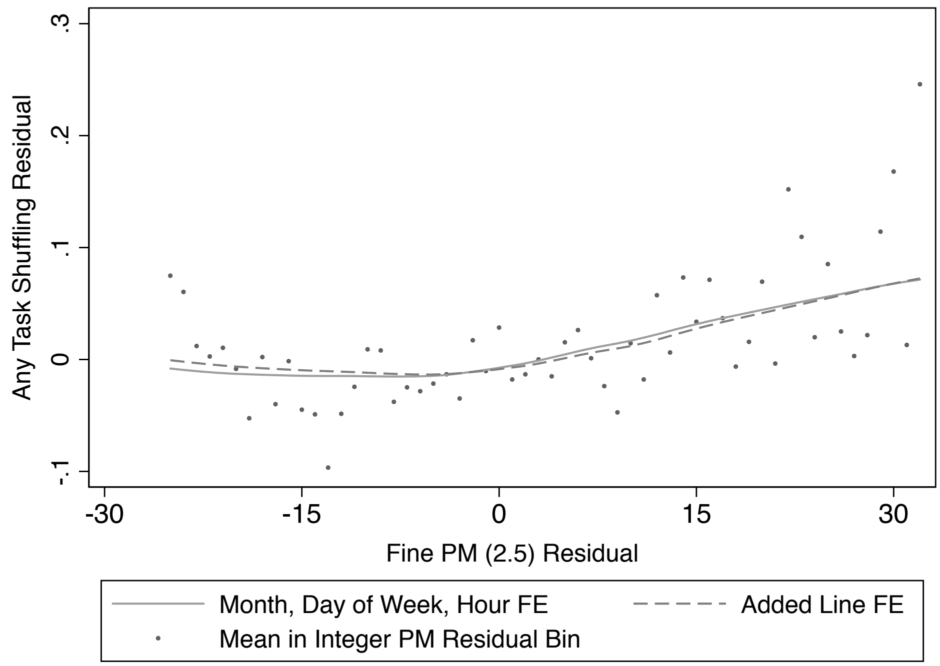


Figure 5 depicts relationship between residuals of fine PM exposure and the dummy for any task shuffling. Residuals are from regressions of each variable on year, month, day of week, and hour of day fixed effects as well as coarse PM. Fine PM residual trimmed at 5th and 95th percentile. Scatter depicts mean residual of task shuffling within integer fine PM residual bins, Lines depict local polynomial smoothing with and without production line fixed effects included in regression producing residuals.

pacts on productivity, but will rather be symmetric in direction at least (if not perfectly in magnitude) around the "expected" level of pollution (or, interchangeably in the model, expected level of worker effort). That is, as pollution increases, task reallocation should increase in response to reoptimize output (i.e., to forego full losses in output due to losses in individual worker productivity) and as pollution decreases task reallocation should *also increase* to reoptimize output (i.e., to capture increases in individual worker productivity).

Accordingly, we replace linear pollution terms with measures of two alternate forms: 1) the absolute value of deviations from median pollution by production floor, day of week, hour of day, month of year, and year), and 2) the above median deviation and absolute value of below median deviation as separate regressors. The graphical relationship between task reallocation and pollution exposure depicted in Figure 5 and the estimates in Table 8 show that indeed task match adjustment increases with pollution exposure, though this seems to be mostly driven by above median pollution values. That is, a change in pollution of one standard deviation from the time and floor-specific median pol-

Table 8: Pollution and Task Match Adjustment

	(1)	(2)	(3)	(4)
	Any Task Match Adjustment			
	1(at least one worker on line reassigned to a different task this hour from last hour)			
Absolute Value Deviations from Median Fine PM	0.02747***		0.02572***	
	(0.00815)		(0.00777)	
Above Median Fine PM Spline		0.03263***		0.03136***
		(0.00877)		(0.00830)
Below Median Fine PM Spline (Absolute Value)		0.00689		0.00406
		(0.01550)		(0.01530)
Coarse PM and Interaction Controls	Absolute Deviations from Median	Above and Below Distance from Median Splines	Absolute Deviations from Median	Above and Below Distance from Median Splines
Line FE	No	Yes	No	Yes
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes
Observations	14,342	14,342	14,342	14,342
Mean of Dependent Variable	0.42			

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

lution increases the probability of any task match adjustment on the line by 2.75 percentage points on average with above median values contributing more than 3 percentage points to the effect. We show next that the small impacts for below median pollution values are driven by heterogeneity in impacts across managerial quality.

6.6 Task Match Adjustment in Response to Pollution by Managerial Quality

The graphical representation of the relationship between task reallocation and pollution exposure for above and below median *Composite Index* managerial quality values depicted in Figure 6 and the analogous regression estimates presented in Table 9 serve as empirical tests of the claim from the theory that higher quality managers engage in significantly more task reallocation in response to pollution than do lower quality measures. Specifically, the highest quality managers are more than 12.5 percentage points more likely to engage in task match adjustment in response to pollution on average than are the lowest quality managers (using composite index estimates); more than 20 percentage points more likely to respond with task reallocation to below median deviations in pollution.

Next, to further support results using specific survey measures and constructed indices for managerial quality presented thus far, we construct a supervisor residual TFP measure as described in section 5 and include the interaction of this measure with the pollution measures as additional terms in the

Table 9: Pollution and Task Match Adjustment by Managerial Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Task Match Adjustment 1(at least one worker on line reassigned to a different task this hour from last hour)					
Production Problem Solving Index X Absolute Val Dev Fine PM	0.02826***					
	(0.00817)					
Monitoring and Reallocation Index X Absolute Val Dev Fine PM			0.05883***			
			(0.02062)			
Composite Index X Absolute Val Dev Fine PM					0.02531***	
					(0.00665)	
Production Problem Solving X Above Median PM Spline		0.03064***				
		(0.00815)				
Production Problem Solving X Below Median PM Spline		0.04764***				
		(0.01668)				
Monitoring and Reallocation X Above Median PM Spline				0.05736***		
				(0.02059)		
Monitoring and Reallocation X Below Median PM Spline				0.09705**		
				(0.03998)		
Composite Index X Above Median Fine PM Spline						0.02623***
						(0.00655)
Composite Index X Below Median Fine PM Spline						0.04265***
						(0.01348)
Absolute Value Deviation from Median Fine PM	-0.03353		-0.06630*		-0.06721**	
	(0.02095)		(0.03423)		(0.02764)	
Above Median Fine PM Spline		-0.03886*		-0.05901*		-0.06874**
		(0.02121)		(0.03439)		(0.02759)
Below Median Fine PM Spline		-0.08641**		-0.14019**		-0.14398***
		(0.03892)		(0.06437)		(0.05223)
Coarse PM Controls and Interactions	Abs Dev	Splines	Abs Dev	Splines	Abs Dev	Splines
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,974	11,974	11,974	11,974	11,974	11,974
Mean of Dependent Variable	0.42					

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the date-hour level. See Table A4 for robustness to within-line correlation in errors.

Table 10: Pollution and Task Match Adjustment by Supervisor Residual TFP

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Task Match Adjustment					
	1(at least one worker on line reassigned to a different task this hour from last hour)					
Supervisor Residual TFP						
Above Median Supervisor TFP X Absolute Val Dev Fine PM	0.11467***		0.11695***		0.11276***	
	(0.01792)		(0.01845)		(0.01819)	
Above Median Supervisor TFP X Above Median PM Spline		0.10349***		0.10354***		0.10161***
		(0.01814)		(0.01914)		(0.01854)
Above Median Supervisor TFP X Below Median PM Spline		0.16852***		0.17660***		0.16558***
		(0.03429)		(0.03364)		(0.03440)
Management Indices						
Production Problem Solving Index X Absolute Val Dev Fine PM	0.01824**					
	(0.00832)					
Monitoring and Reallocation Index X Absolute Val Dev Fine PM			0.02730			
			(0.02161)			
Composite Index X Absolute Val Dev Fine PM					0.01540**	
					(0.00683)	
Production Problem Solving X Above Median PM Spline		0.01066				
		(0.00858)				
Production Problem Solving X Below Median PM Spline		0.03933**				
		(0.01745)				
Monitoring and Reallocation X Above Median PM Spline				0.03479		
				(0.02266)		
Monitoring and Reallocation X Below Median PM Spline				0.02461		
				(0.04211)		
Composite Index X Above Median Fine PM Spline						0.01097
						(0.00708)
Composite Index X Below Median Fine PM Spline						0.02999**
						(0.01425)
Fine and Coarse PM Controls and Coarse PM Interactions	Abs Dev	Splines	Abs Dev	Splines	Abs Dev	Splines
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,974	11,974	11,974	11,974	11,974	11,974
Mean of Dependent Variable	0.42					

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

Figure 6

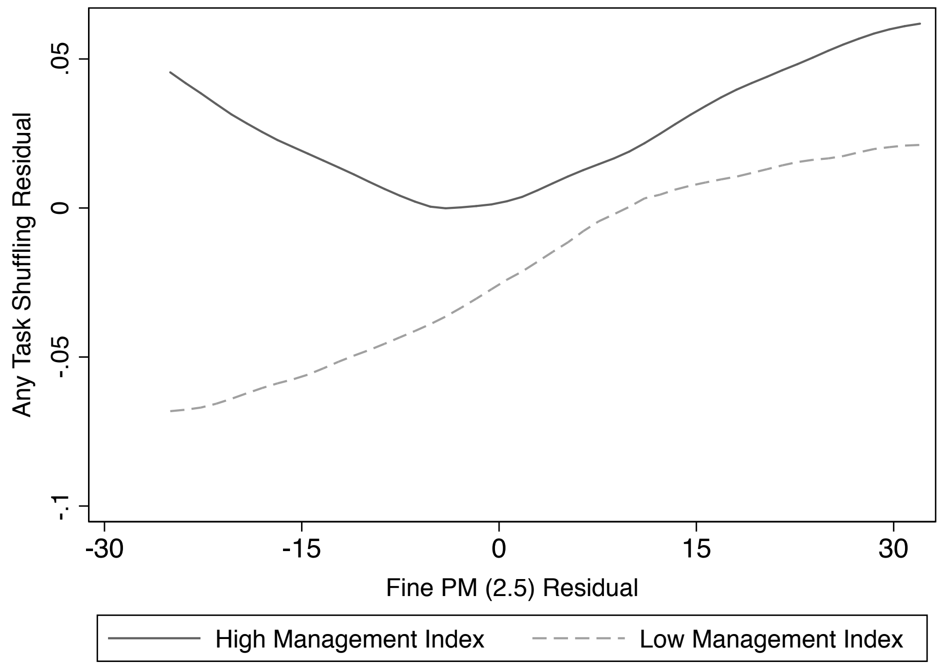


Figure 6 depicts relationship between residuals of fine PM exposure and dummy for any task shuffling by high and low managerial quality. High management corresponds to above median Composite Index; low management to below median. Residuals are from regressions of each variable on year, month, day of week, and hour of day fixed effects as well as coarse PM. Fine PM residual trimmed at 5th and 95th percentile. Lines depict local polynomial smoothing.

otherwise identical specification reported in Table 9. These results are reported in Table 10 and show that "better" managers as defined by the residual productivity of the lines they supervise respond to pollution with task reallocation in much the same way as do higher quality managers as defined by our indices. However, rather interestingly, the inclusion of this strong residual productivity quality measure does not fully absorb or obviate the impacts of our original managerial quality indices. Indeed, the managerial index coefficients remain significant in many specifications and roughly 50 to 60% the magnitude of those in Table 9. We interpret these results as strong evidence in support of the validity of our managerial quality measures as well as evidence that these measures contain information not immediately observable from productivity data alone. Next, we investigate what the additional information in the managerial quality indices might actually be and what personality or management style traits might predict higher managerial quality.

Table 11: Partial Correlations with Supervisor Residual TFP and Managerial Quality Indices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Supervisor Residual TFP Residual from regression of ln(pieces produced) on worker and time FE				Production Problem Solving Index	Monitoring and Reallocation Index	Composite Index
Production Problem Solving Index	0.00345						
	(0.00712)						
Monitoring and Reallocation Index		0.04827**					
		(0.01691)					
Composite Index			0.00802				
			(0.00713)				
Management Practices							
Meeting Targets (ME)				-0.04175	0.12138***	0.00347	0.12485**
				(0.03238)	(0.04586)	(0.03578)	(0.05770)
Encouraging Star Performers (ME)				0.01218	0.09348*	0.22143***	0.31491***
				(0.02475)	(0.05209)	(0.04064)	(0.06554)
Keeping Talented Workers (ME)				0.02827**	0.09931**	0.06349*	0.16280***
				(0.00955)	(0.04889)	(0.03814)	(0.06151)
Management Style							
Positive Leadership Behavior (ME)				-0.02701	0.11269**	0.04808	0.16077***
				(0.01520)	(0.04700)	(0.03666)	(0.05913)
Passive Conflict Resolution Style (ME)				-0.00114	-0.08840*	-0.08603**	-0.17444***
				(0.02322)	(0.04776)	(0.03726)	(0.06009)
Personality							
Conscientiousness (ME)				-0.02590	0.08690*	0.07661*	0.16351**
				(0.02159)	(0.05137)	(0.04007)	(0.06463)
Locus of Control (ME)				-0.00362	-0.02683	-0.04518	-0.07201
				(0.01786)	(0.03694)	(0.02882)	(0.04648)
Perseverance (ME)				0.02203	0.07269	0.02086	0.09355
				(0.01833)	(0.04877)	(0.03805)	(0.06136)
Self-Esteem (ME)				0.02223	-0.03549	-0.04102	-0.07651
				(0.01434)	(0.04746)	(0.03703)	(0.05972)
Observations	1,649	1,649	1,649	1,649	473	473	473
SD of Dependent Variable	0.72				0.76	0.60	1.06
Mean of Dependent Variable	0.00				2.26	1.46	3.71

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

6.7 Managerial Quality Unpacked: Practices, Skills, and Personality

In Table 11 we report estimates of partial correlations from descriptive regressions relating the managerial indices to supervisor residual TFP and to additional measures from the management survey of management practices, management style, and personality traits. Columns 1 through 4 of Table 11 show that in fact our managerial quality indices are positively correlated with the supervisor residual TFP measure, but this correlation is small and somewhat weak. Column 5 shows that in fact many other survey measures for management practices, style, and personality traits are equally weakly correlated with supervisor residual TFP. On the other hand, we find that many of these measures are strongly correlated with our managerial quality indices. In particular, we find that the more specific practices the manager reports engaging in to meet targets, positively reinforce high performing workers, and retain these high performing workers, the higher the managerial quality as measured by all of our indices. Additionally, positive leadership behaviors and less passive conflict resolution correlate positively with our indices.

Personality measures in general show weaker correlations, but we find some evidence that conscientiousness is positively correlated with all of our managerial indices. We interpret these results as further evidence that our managerial quality indices have incremental information beyond what is directly observable in average productivity alone and are important determinants of production decisions in general as well as determinants specifically of responses to productivity shocks.

7 Conclusion

Managerial quality has been shown to be a crucial determinant of firm and worker productivity. In this paper, we model the role of managerial quality on productivity via the re-optimization of production in response to worker and task-specific productivity shocks. We estimate the model using data on hourly individual productivity, managerial quality, and high frequency fluctuations in air pollution, which negatively impacts productivity. We note the presence of intra-firm heterogeneity on two important aspects of management – optimizing the assignment of workers to tasks and identifying and resolving production issues - and estimate the impact of this heterogeneity on productivity.

We show that not only do higher quality managers achieve higher productivity on average, they are able to avoid losses from negative productivity shocks caused by air pollution through re-optimization of worker-task matching. Lines supervised by the highest quality managers suffer much smaller losses as a result of air pollution productivity shocks by way of more dynamic worker reallocation.

We validate our measures of managerial quality using residual productivity measures of supervisor TFP, and establish the incremental value of such measures of managerial quality above and beyond measures of observable productivity. We also provide descriptive evidence of the specific practices, management styles, and personality traits that contribute to managerial quality index values. These results contribute to explaining the mechanisms through which managerial inattention impacts productivity.

Our results hopefully also prompt further questions to be explored in future work. In particular, whether these aspects of quality are immutable, or responsive to training is an important question, as is the question of whether managers with similar goals respond differently to different incentive structures. While these are outside the scope of this study, they form interesting questions for future work.

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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. 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: Daily PM

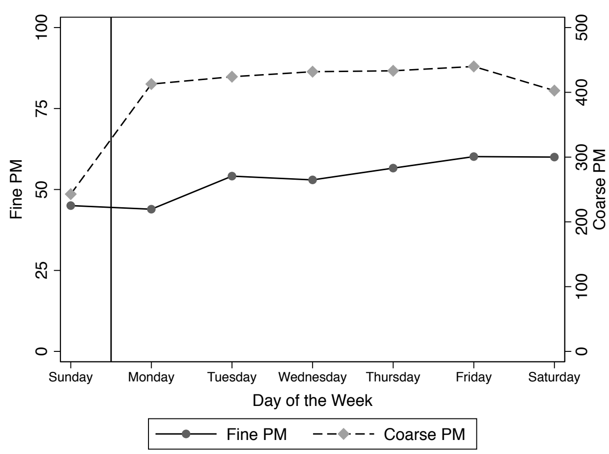
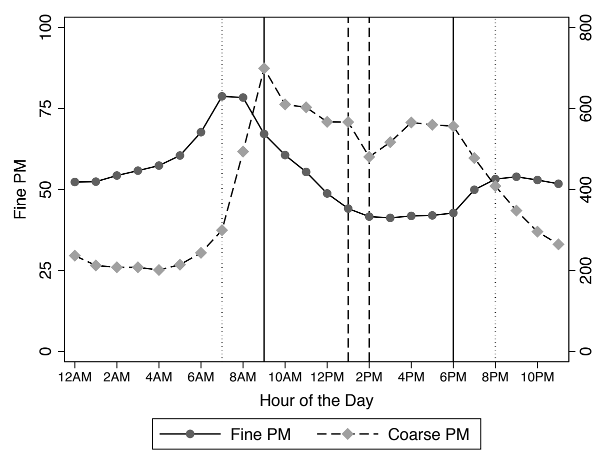


Figure A2: Hourly PM



Figures A1 and A2 depict mean of fine and coarse PM levels across days of the week (A1) and hours of the day (A2). Vertical line denotes start of production week in Figure A1. In Figure A2, vertical solid lines denote start and end of production day; dashed lines denote lunch hour; and dotted lines commuting hours.

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

In Table A2, we show robustness of estimates from Table 5 to the inclusion of additional controls for weather. We find that the results are nearly unaffected by these additional controls.

In Table A3, we show robustness of estimates from Table 7 to various estimators that allow for differing types of within-line correlation in errors. The random effect estimator allows for errors to be

Table A1: Managerial Quality Indices Summary Statistics

	Frequency	Percent	Cummulative
Production Problem Solving Index			
0	1,144	9.55	9.55
1	1,161	9.7	19.25
1.5	2,113	17.65	36.9
2	195	1.63	38.53
2.333333	838	7	45.52
2.5	2,229	18.62	64.14
2.666667	1,110	9.27	73.41
3	3,184	26.59	100
Monitoring and Reallocation Index			
0.5	174	1.45	1.45
1	2,306	19.26	20.71
1.333333	1,110	9.27	29.98
1.5	3,189	26.63	56.61
1.666667	838	7	63.61
2	4,357	36.39	100
Composite Index			
1	1144	9.55	9.55
2.5	1335	11.15	20.7
3	970	8.10	28.8
3.5	2305	19.25	48.05
4	1948	16.27	64.32
4.5	2167	18.10	82.42
5	2105	17.58	100

	Production Problem Solving	Monitoring and Shuffling	Composite
Pairwise Correlation			
Production Problem Solving Index	1		
Monitoring and Reallocation Index	0.3999	1	
Composite Index	0.9502	0.6657	1

Table A2: Pollution and Productivity by Managerial Quality (Robustness to Weather Controls)

	(1)	(2)	(3)
	Any Task Match Adjustment 1(at least one worker on line reassigned to a different task this hour from last hour)		
Random Effects (Equicorrelated Within Line)			
Production Problem Solving Index X Abs Val Dev Fine PM	0.00108***		
	(0.00034)		
Monitoring and Reallocation Index X Abs Val Dev Fine PM		0.00225***	
		(0.00085)	
Composite Index X Fine PM			0.00097***
			(0.00028)
GLS (Line-specific AR(1))			
Production Problem Solving Index X Abs Val Dev Fine PM	0.00084***		
	(0.00032)		
Monitoring and Reallocation Index X Abs Val Dev Fine PM		0.00114	
		(0.00080)	
Composite Index X Abs Val Dev Fine PM			0.00070***
			(0.00027)
Fine and Coarse PM Controls	Above and Below Median Absolute Value Deviation Splines		
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes
Observations	11,974	11,974	11,974
Mean of Dependent Variable		0.42	

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Errors estimated according to models described in each panel above.

correlated within line over time, but assumes this correlation is fixed. This assumption is likely true conditional on the full set of time fixed effects included in all specifications. The GLS model reported allows for a line-specific AR(1) process in the errors, relaxing the assumption in the random effects model. The GLS model is however less efficient under the random effects assumptions. We find that the overall pattern of results as well as statistical significance is generally preserved.

In Table A4, we show robustness of estimates from Table 9 to the same estimators from Table A3 that allow for differing types of within-line correlation in errors. Once again, we find that the overall pattern of results as well as statistical significance is generally preserved.

Table A3: Managerial Quality and Line Productivity (Robustness to Within-Line Correlation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pieces Produced pieces produced by worker this hour				Efficiency (pieces produced / target pieces)			
Fine PM (Std)	-0.59952***	-0.68705***	-0.58913***	-1.57081***	-0.54561***	-0.65591***	-0.54455***	-1.43305***
	(0.14326)	(0.17938)	(0.21790)	(0.26647)	(0.14467)	(0.16847)	(0.20907)	(0.23903)
Additional Weather Controls	Date FE	Mean Daily Temp	Daily Temp & Rain	Hourly Temp and Rel Hum	Date FE	Mean Daily Temp	Daily Temp & Rain	Hourly Temp and Rel Hum
Coarse PM Controls	Linear							
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	1,054,962	1,054,962	493,521	392,009	1,054,962	1,054,962	493,521	392,009

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

Table A4: Pollution and Task Match Adjustment by Managerial Quality (Robustness to Within-Line Correlation)

	(1)	(2)	(3)	(4)	(5)	(6)
	Pieces Produced mean(pieces produced by workers on line within hour)			Efficiency mean(pieces produced / target pieces)		
Random Effects (Equicorrelated Within Line)						
Production Problem Solving Index X Fine PM	0.01865***			0.01995***		
	(0.00514)			(0.00504)		
Monitoring and Reallocation Index X Fine PM		0.04208***			0.04189***	
		(0.01196)			(0.01171)	
Composite Index X Fine PM			0.01738***			0.01815***
			(0.00422)			(0.00414)
GLS (Line-specific AR(1))						
Production Problem Solving Index X Fine PM	0.00962**			0.00896**		
	(0.00412)			(0.00404)		
Monitoring and Reallocation Index X Fine PM		0.00265			0.00920	
		(0.00940)			(0.00924)	
Composite Index X Fine PM			0.00675**			0.00710**
			(0.00340)			(0.00334)
Fine and Coarse PM Controls	Linear					
Year, Month, Day-of-Week, Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,974	11,974	11,974	11,974	11,974	11,974
Mean of Dependent Variable		50.38			48.82	

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Errors estimated according to models described in each panel above.

B Data Appendix

B.1 Productivity and other Production Variables

- *Pieces Produced*: Number of garments produced at the hourly level (per worker or per line depending on the regression specification). Line-level number of garments in a given hour is the average of the number of garments produced at the worker-level.

- *Standard Allowable Minutes (SAM)*: This is a measure of how many minutes a particular garment style should be completed in. For instance, a garment style with a SAM of .5 is deemed to take a half minute to produce one complete garment. It is a standardized measure across the global garment industry and is drawn from an industrial engineering database, although it might be amended to account for stylistic variations from the representative garment style in the database.

- *Target Quantity*: The target quantity for a given unit of time for a line producing a particular style is 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 $\frac{60}{0.5} = 120$ garments per hour.

- *Efficiency*: $\left(\frac{\text{Number of garments produced}}{\text{Number of target garments}}\right)$*100 at the hourly level (per worker or per line depending on the regression specification). Line-level number efficiency in a given hour is the mean of worker-level efficiency in that hour.

B.2 Worker Task Adjustment

- *Any Task Match Adjustment*: 1[any worker was reassigned on the line to a different task than they were doing the previous hour].

B.3 Worker Position in the Line

- *Seat in Line*: This indicates the relative placement of the worker in the line in order of the flow of production. e.g. the worker conducting the first operation in the production process is said to be in seat 1, the worker next to him who takes worker 1's production and adds to it in seat 2, and so on.

B.4 Pollution

- *Fine PM(Std)*: Fine (0.5-2.5 microns in diameter) particulate matter (PM) concentration ($\mu g/m^3$)/SD(fine PM concentration)

- *Coarse PM(Std)*: Coarse (2.5-10 microns in diameter) particulate matter (PM) concentration ($\mu g/m^3$)/SD(coarse PM concentration)

B.5 Management

B.5.1 Managerial Quality

- *Production Problem Solving Index (0-3)*: It is the sum of the following three indicator variables, and ranges from 0 to 3 (if the line is supervised by more than one supervisor, the indicators are averaged across supervisors before summing to construct the index).

  - 1[supervisor generally learns about production issues from talking to workers].
  - 1[supervisor is fluent in the native language of the majority of the workers]
  - 1[whether the supervisor generally solves production issues on their own]

- *Monitoring and Reallocation Index (0-2)*: It is the sum of the following two indicator variables, and so ranges from 0 to 2.

  - 1[reported making rounds of the line to monitor production at least every 10 min]. If the line is supervised by more than one supervisor, the minimum value is taken to maximize the variation in this variable.
  - 1[reported that they would try to replace a worker that was performing poorly]. If the line is supervised by more than one supervisor, the indicators are averaged across supervisors before summing to construct the index.

- *Composite Index (0-5)*: The sum of the Production Problem Solving Index and the Monitoring and Reallocation Index. It is the sum of the five indicator variables comprising these indices, and so ranges from 0 to 5.

B.5.2 Other Management Variables

- *Supervisor TFP Residual*: This is constructing by regressing log(pieces produced) [20] at the worker-level on all time fixed effects (Year, Month, Day-of-Week, Hour-of-Day FE) and worker fixed effects, and constructing average line level predicted residuals.

- *Meeting Targets (ME)*: This measure captures the effort exerted by supervisors in meeting targets. Supervisors were asked what practices they follow to ensure production targets are met. Each practice was coded as an indicator variable and comprised of the following indicators:

  - 1[Do rounds of the line to ensure things are in order]
  - 1[Talk to workers individually]
  - 1[Provide positive reinforcement to high-performing workers]
  - 1[Make low-performing workers aware of their work]
  - 1[Demonstrate how to work by example]

  The final measure was computed as the mean effect normalization of these five indicator variables.[21]

- *Encouraging Star Performers (ME)*: This measure captures the effort exerted by supervisors in encouraging and retaining high performing workers on their line. Supervisors were asked what practices they follow to encourage a worker who was very productive and fulfilled their targets in a timely manner. Each practice was coded as an indicator variable and comprised of the following indicators:

  - 1[Commend the worker on their work/effort]
  - 1[Praise the worker in presence of other workers]
  - 1[Put in good word for workers to upper-level management]
  - 1[Recommend the worker for a promotion]
  - 1[Other]

[20] to correspond to the log-linearized Cobb-Douglas production function

[21] The mean effect normalization is calculated by subtracting the mean and dividing the standard deviation for each indicator variable, adding up these normalized variables, and then subtracting the mean and dividing the standard deviation for this composite variable. While this maximizes the variation in the variable, using the simple sum of the binary variables does not significantly alter the results using this variable.

The final measure was computed as the mean effect normalization of the above indicator variables.

- *Keeping Talented Workers (ME)*: This measure captures the effort exerted by supervisors in retaining high performing workers on their line. Supervisors were asked what practices they follow to retain a very productive worker who wanted to leave the company . Each practice was coded as an indicator variable and comprised of the following indicators:

  – 1[Talk to the worker directly to convince them to stay]

  – 1[Put in good word for the worker to upper-level management]

  – 1[Recommend a salary increase for the worker]

  – 1[Recommend the worker for a promotion]

  – 1[Other]

  The final measure was computed as the mean effect normalization of the above variables.

- *Positive Leadership Behavior(ME)*: This measure captures the net number of behaviors supervisors identify engaging in that can be described as positive management behaviors. Supervisors were asked about the extent (measured on a 5-point scale of agreement ranging from Strongly Agree to Strongly Disagree) to which they engaged in 18 positive and 6 negative behaviors. The score from each variable was added up for positive and negative behaviors and the score from the negative behaviors was then subtracted from the score for positive behaviors.

  The positive practices were the following:

  – I do personal favors for workers in my line

  – I make my attitudes clear to the workers in my line

  – I do little things to make it pleasant to be a member of my line

  – I try out new ideas with my line

  – I act as the real leader of the line

  – I am easy to understand

  – I find time to listen to members of the line

  – I give advance notice of changes

- I look out for the personal welfare of individual workers on my line
- I assign workers on the line to particular tasks clearly
- I am the spokesman of the line
- I schedule the work to be done
- I maintain definite standards of performance
- I keep the line informed
- I back up the workers in my line in their actions
- I emphasize the meeting of deadlines
- I treat all workers in my line as my equals
- I encourage the use of uniform procedures

The negative practices were the following:

- I rule with an iron fist
- I criticize poor work
- I speak in a manner not to be questioned
- I keep to myself
- I refuse to explain my actions
- I act without consulting the line

The final measure was computed as the mean effect normalization of the above variables.

• *Passive Conflict Resolution Style (ME)*: This measure captures the style followed by supervisors in resolving conflicts arising during the management process. Supervisors were asked about the frequency (measured on a 5-point scale of frequency ranging from Very Frequently to Very Infrequently)with which they had engaged in the following conflict resolution behaviors:

  - Management problems with employees
  - Had direct reports (workers who reported to that supervisor) that resisted their initiatives
  - Had interpersonal conflicts between them and at least one of their direct reports

  - Had employees who were used to doing things they way they had been done and were reluctant to change
  - Had key members of your staff that were incompetent, unmotivated, technically obsolete, or otherwise poor performers
  - Had key direct reports that lacked the experience to do their jobs without close supervision

  The final measure was computed as the mean effect normalization of the above variables.

- *Contentiousness (ME)*: This measure captures the net number of behaviors supervisors identify with that are predictive of contentiousness. Supervisors were asked about the extent (measured on a 5-point scale of agreement ranging from Strongly Agree to Strongly Disagree) to which they engaged in 5 positive and 5 negative behaviors. The score from each variable was added up for positive and negative behaviors and the score from the negative behaviors was then subtracted from the score for positive behaviors.

  The positive behaviors were the following:

  - I am always prepared
  - I pay attention to details
  - I get chores done right away
  - I carry out my plans
  - I make plans and stick to them

  The negative behaviors were the following:

  - I procrastinate and waste my time
  - I find it difficult to get down to work
  - I do just enough work to get by
  - I don't see things through
  - I shirk my duties

  The final measure was computed as the mean effect normalization of the above variables.

- *Locus of Control (ME)*: This measure captures the net number of beliefs supervisors identify with that are predictive of locus of control. Supervisors were asked about the extent (measured on a 5-point scale of agreement ranging from Strongly Agree to Strongly Disagree) to which they believed 5 statements, one of which is positively related to locus of control and four which are negatively related. The score from each variable was added up for the negative statements and the score from the negative statements was then subtracted from the score for positive statement.

  The positive statement was the following:

  – I believe that my success depends on ability rather than luck

  The negative statements were the following:

  – I believe that unfortunate events occur because of bad luck
  – I believe that the world is controlled by a few powerful people
  – I believe some people are born lucky
  – I believe in the power of fate

  The final measure was computed as the mean effect normalization of the above variables.

- *Perseverance (ME)*: This measure captures the net number of behaviors supervisors engage in that are predictive of perseverance. Supervisors were asked about the extent (measured on a 5-point scale of agreement ranging from Strongly Agree to Strongly Disagree) to which they engaged in 8 behaviors, five of which is positively related to perseverance and three which are negatively related. The score from each variable was added up for the negative statements and the score from the negative behaviors was then subtracted from the score for positive behaviors.

  The positive behaviors were the following:

  – I don't quit a task before it is finished
  – I am a goal-oriented person
  – I finish things despite obstacles in the way
  – I am a hard worker
  – I don't get sidetracked when I work

  The negative behaviors were the following:

- I don't finish what I start
- I give up easily
- I do not tend to stick with what I decide to do

The final measure was computed as the mean effect normalization of the above variables.

- *Self-Esteem (ME)*: This measure captures the net number of beliefs supervisors identify with that are predictive of self-esteem. Supervisors were asked about the extent (measured on a 5-point scale of agreement ranging from Strongly Agree to Strongly Disagree) to which they believed 10 statements, five of which is positively related to self-esteem and four which are negatively related. The score from each variable was added up for the negative statements and the score from the negative statements was then subtracted from the score for positive statements.

  The positive statements were the following:

  - On the whole, I am satisfied with myself
  - I feel that I have a number of good qualities
  - I am able to do things as well as most other people
  - I feel that I am person of worth, at least on an equal plane with others
  - I take a positive attitude toward myself

  The negative statements were the following:

  - I feel I do not have much to be proud of
  - At times, I think I am no good at all
  - I certainly feel useless at times
  - I wish I could have more respect for myself
  - All in all, I am inclined to feel that I am a failure

  The final measure was computed as the mean effect normalization of the above variables.