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## **NO LINE LEFT BEHIND: ASSORTATIVE MATCHING INSIDE THE FIRM**

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Achyuta Adhvaryu

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# NO LINE LEFT BEHIND: ASSORTATIVE MATCHING INSIDE THE FIRM

## Abstract

How do firms pair workers with managers, and which constraints affect the allocation of labor within the firm? We characterize the sorting pattern of managers to workers in a large readymade garment manufacturer in India, and then explore potential drivers of the observed allocation. Workers in this firm are organized into production lines, each supervised by a manager. We exploit the high degree of worker mobility across lines, together with worker-level productivity data, to estimate the sorting of workers to managers. We find negative assortative matching (NAM) -- that is, better managers tend to match with worse workers, and vice versa. This stands in contrast to our estimates of the production technology, which reveal that if the firm were to positively sort, productivity would increase by 1 to 4 percent across the six factories in our data. Coupling these findings with a survey of managers and with data on multinational brands and the orders they place, we document that NAM arises, at least in part, because the value of buyer relationships imposes minimum productivity constraints on each production line. Our results emphasize that suppliers to the global market, when they are beholden to a small set of powerful buyers, may be driven to allocate managerial skill to service these relationships, even at the expense of productivity.

JEL Classification: J24, L14, L23, M5

Keywords: assortative matching, Management, productivity, Global Buyers, Readymade Garments, India

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# No Line Left Behind: Assortative Matching Inside the Firm\*

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March 27, 2020

## Abstract

How do firms pair workers with managers, and which constraints affect the allocation of labor within the firm? We characterize the sorting pattern of managers to workers in a large readymade garment manufacturer in India, and then explore potential drivers of the observed allocation. Workers in this firm are organized into production lines, each supervised by a manager. We exploit the high degree of worker mobility across lines, together with worker-level productivity data, to estimate the sorting of workers to managers. We find negative assortative matching (NAM) – that is, better managers tend to match with worse workers, and vice versa. This stands in contrast to our estimates of the production technology, which reveal that if the firm were to positively sort, productivity would increase by 1 to 4 percent across the six factories in our data. Coupling these findings with a survey of managers and with data on multinational brands and the orders they place, we document that NAM arises, at least in part, because the value of buyer relationships imposes minimum productivity constraints on each production line. Our results emphasize that suppliers to the global market, when they are beholden to a small set of powerful buyers, may be driven to allocate managerial skill to service these relationships, even at the expense of productivity.

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# 1 Introduction

How are managers matched with workers in production teams within a firm? Are the best managers paired with the best workers, or with those workers who are struggling to perform? These questions are at the core of organizational economics (Lazear and Oyer, 2007; Lazear and Shaw, 2007). A great deal of theoretical work studies the nature of this type of firm decision-making and illustrates the implications for firm productivity and growth (Garicano and Rossi-Hansberg, 2006; Holmstrom and Tirole, 1989; Kremer, 1993).

Recent empirical evidence affirms that what makes a good worker is often not what makes a good manager, and as such manager and worker skills are not likely substitutable in the production function (Benson et al., 2018). Rather, studies have shown that good managers likely amplify the productive value of good workers, by way of retention (Hoffman and Tadelis, 2019; Lazear et al., 2015), effort elicitation (Frederiksen et al., 2019), and task assignment (Adhvaryu et al., 2019a). Absent other considerations, a firm aiming to allocate managers and workers to production teams to maximize output would positively sort the best managers to the best workers. However, little evidence exists as to whether this is what firms do in practice, and on the constraints that shape the internal allocation of labor.<sup>1</sup>

In this paper we leverage over three years of daily data on worker-level productivity and team composition from a large Indian manufacturer to estimate the pattern of sorting of managers to workers within the firm, and how this determines firm productivity. We then exploit a novel survey of managers that we conducted, together with data on the orders that large international buyers place at this firm, to shed light on which constraints affect the allocation of labor within the firm. Our key contribution is to highlight how constraints related to the nature of global supply chains shape the productivity of the firm by affecting the internal allocation of labor.

Our data comes from six factories of a large readymade garment manufacturer in India. Workers in this firm are organized into production lines producing orders placed by international buyers, with each line supervised by a manager. Worker mobility across lines is very high, both monthly – as orders and resulting labor needs change – and daily – as absenteeism leads to critical manpower

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<sup>1</sup>Some recent studies describe the pattern of high-level managers (e.g., CEOs) matching *across* firms (Bandiera et al., 2015, 2019), but little evidence exists documenting and explaining realized patterns of how middle managers match to production teams *within* the firm due to stringent data requirements.

shortages on some lines. This high frequency shuffling of workers across lines, along with granular worker-level productivity data, allows us to document the pattern of sorting of managers to workers.

We estimate worker and manager fixed effects from a two-way fixed effects model in the spirit of Abowd et al. (1999). Previous studies of worker sorting have focused on labor market level sorting of workers *across* firms using *wages* (Card et al., 2013; Lopes de Melo, 2018). We extend this approach to the estimation of sorting *within* the firm, leveraging granular data on *productivity* rather than wages. We note that the identification issues that arise when using wages (Eeckhout and Kircher, 2011; Hagedorn et al., 2017) do not apply when productivity is observable as is often the case in firm personnel data. We find that, on average across the six factories in our data, the correlation between these worker and manager fixed effects is  $-16\%$ , indicating negative assortative matching (NAM). That is, better managers tend to match with worse workers, and vice versa.<sup>2</sup>

These results are notable in that they contrast with most matching patterns obtained from studies of the sorting of workers across firms (Abowd et al., 1999; Card et al., 2018, 2013; Eeckhout, 2018) and are inconsistent with the hypothesized complementarity (or imperfect substitutability) between worker and manager skill, which should generate *positive* assortative matching (PAM) (Bandiera et al., 2007, 2009; Lazear et al., 2015). This begs the question whether the pattern of NAM arises as the result of productivity maximization or if other intervening concerns might be driving the observed pattern in practice. In order to assess this, we investigate how the skill of managers and workers combine to determine team productivity.

We perform a series of tests to verify that the production function is in fact additively separable in logs, which is consistent with the underlying technology exhibiting a positive cross-partial derivative between worker and manager skill in levels. This implies that a given worker’s productivity *increases* in her manager’s type, and so – absent other constraints in production – total productivity would be maximized by implementing positive assortative matching between workers and managers. This is confirmed by the results of a counterfactual exercise. Specifically, using our estimates of the worker and manager fixed effects, we simulate total productivity under the perfect positive assortative matching allocation between workers and managers. We find that indeed total productivity would

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<sup>2</sup>Given common concerns regarding limited mobility bias when using these estimation procedures, we check that our results are robust to using standard bias correction methods (Abowd et al., 2004; Andrews et al., 2008, 2012) as well as to performing the latest covariance shrinkage methods developed by Best et al. (2019). The robustness of our results is consistent with the large degree of mobility in our data relative to other studies.

increase by between 1-4% across the factories in our sample under this counterfactual allocation. This suggests that the shape of the underlying production technology cannot be an explanation for the observed pattern of *negative* sorting on average.<sup>3</sup>

We hypothesize that negative matching arises because of strong incentives to avoid delays in completing any particular order. That is, the firm is willing to forfeit some productivity to ensure that minimum productivity on least productive lines does not fall so low as to delay completion and delivery of an order. Delays of this sort can severely damage the relationship between the manufacturer and the brand buyer, leading to less favorable future contracts and in the extreme, termination of the relationship, thus harming firm profits.

We conduct a novel survey of managers to assess the importance of these considerations. We find that managers report substantial concerns related to their lines falling behind in production and not meeting the deadlines set by brand buyers. When asked about what strategies managers adopt to try and avoid having lines fall behind, 91% say that they would move workers across production lines to help the low-performing lines catch up, and in almost all cases they would move a *high*-productivity worker to a *low*-productivity line. This is exactly the pattern of moves that would generate NAM. We also show that factories where managers are most worried about falling behind on orders and not meeting deadlines with buyers are indeed the ones where negative sorting is strongest.

Finally, using data on global buyers and the orders they place with this supplier, we find that the degree of NAM is stronger on orders placed by the largest buyers. Relationships with such buyers are particularly valuable to the firm, and so this provides further evidence that NAM arises, at least in part, as a response to supply chain constraints with large and important buyers. Interestingly, we further document that the degree of assortative matching becomes less negative over time. This is in line with such supply chain constraints becoming less binding once reputation has been established, which matches evidence on the evolution of buyer-supplier relationships in similar settings (Macchiavello and Morjaria, 2015).

Our results highlight how trade frictions shape production decisions at the firm level. In particular, they suggest that the presence of underlying constraints related to the nature of supply

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<sup>3</sup>These results emphasize the distinction between empirical estimates of sorting and the shape of the underlying production function (Eeckhout and Kircher, 2011).

chains (i.e., the risk of damaging valuable relationships with buyers) prevents firms from fully exploiting complementarities in production. The results of our counterfactual exercise provide an estimate of the magnitude of these constraints: the firm is willing to sacrifice between 1-4% of productivity to safeguard these important relationships. These findings likely generalize to the global supply chain for many products, in which suppliers produce orders for multiple buyers, but an imperfectly competitive market might hold suppliers inside their production frontier as they strive to protect valuable relationships with buyers. That is, when buyer relationships hold substantial value, profit maximization may not equate to productivity maximization for suppliers.<sup>4</sup>

This evidence complements recent empirical work in the literature on trade and development documenting how prices and quantities reflect the importance of these global buyer relationships to developing country suppliers (Macchiavello and Morjaria, 2015), and how the features of these relationships determine suppliers' markups and marginal cost (Cajal Grossi et al., 2019). We add evidence that production and personnel decisions can reflect buyer relationship considerations as well, and that suppliers might even forfeit productivity to maintain relationships with buyers. This stands in contrast to recent evidence of learning-by-exporting (Atkin et al., 2017), in that we document one way in which buyer relationships might *reduce* supplier productivity.<sup>5</sup>

This study advances the organizational economics literature by documenting how manager and worker skills are distributed within the firm, and how this in turn determines firm productivity. An emerging body of empirical work in personnel economics has begun to inform how co-workers impact each other's productivities (Amodio and Martinez-Carrasco, 2018; Boning et al., 2007; Hamilton et al., 2003), as well as how the interaction between workers and their supervisors determines firm productivity (Adhvaryu et al., 2019b; Frederiksen et al., 2019; Hoffman and Tadelis, 2019; Lazear et al., 2015). In addition, a few related papers document the pattern of matching of high level managers like CEOs *across* firms (Bandiera et al., 2015, 2019). We add to these related literatures by providing direct evidence on the sorting pattern of managers to workers *within* a firm. In doing so, we document that the realized pattern of negative sorting between workers and managers does

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<sup>4</sup>Interestingly, a recent study finds a similar pattern of negative assortative matching of managers to teams, at the expense of productivity maximization, in a public sector setting where analogous minimum productivity constraints may arise for different reasons (Fenizia, 2019).

<sup>5</sup>More broadly, our results are in line with the findings of a recent literature in international trade, which finds that international buyers based in high-income countries exert substantial market power with their suppliers (Morlacco, 2019).



not reflect the most productive possible match, and highlight competing considerations that affect team composition.

We also extend a rich empirical literature on management and productivity (Adhvaryu et al., 2019b; Bloom and Van Reenen, 2007, 2011; McKenzie and Woodruff, 2016). Recent experimental studies have convincingly proven that increasing managerial quality can increase the productivity of the firm (Bloom et al., 2013, 2018; Karlan et al., 2015; McKenzie and Woodruff, 2013).<sup>6</sup> However, less attention has been devoted to how firms allocate the existing stock of managerial skills across workers within the firm, and how this determines productivity.<sup>7</sup> Our results emphasize another way in which managerial quality may contribute to low productivity in developing country settings. That is, not only is the stock of managerial skill low, but the existing stock may not be properly allocated to maximize productivity. Suppliers to the global market, concentrated in developing countries, may be beholden to a small set of powerful buyers from developed countries. Accordingly, suppliers may be driven to allocate managerial skill to service of these relationships, even at the expense of productivity.<sup>8</sup>

The rest of the paper is organized as follows. In Section 2 we describe the setting and data. In Section 3 we present estimates of the sorting pattern of managers to workers. Section 4 explores the potential drivers of the estimated sorting pattern, focusing on the role of the underlying production technology and constraints related to supply chains with international buyers. In Section 5 we perform a counterfactual simulation to study the potential productivity gains from labor reallocation. Section 6 concludes.

## 2 Context, Data and Descriptives

In this section, we describe the setting where our study takes place and the data used for estimation. We then present descriptive evidence on the degree of mobility of workers across managers, as well

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<sup>6</sup>Middle managers like the production line supervisors we study are often emphasized as enablers or constrainers of worker productivity (Adhvaryu et al., 2019b; Levitt et al., 2013), particularly in low income countries and labor-intensive manufacturing settings (Blattman and Dercon, 2018; Bloom and Van Reenen, 2007; McKenzie and Woodruff, 2016).

<sup>7</sup>Understanding how best to utilize the managerial talent firms already possess is particularly important in developing countries like India, where limited trust outside the family and information frictions impede hiring from the external labor market (Adhvaryu et al., 2018; Bassi and Nansamba, 2019; Bloom et al., 2010).

<sup>8</sup>Notably, Bandiera et al. (2019) find that high level managers like CEOs are, to some degree, misallocated *across* firms in developing countries like India as well.

as on productivity dispersion across workers and managers. As described later in the paper, a high degree of mobility and substantial dispersion in productivity are necessary to recover the pattern of sorting of managers to workers with the estimation procedure we follow.

## 2.1 Context and Organization of Production

We study the sorting of workers to managers in six ready-made garment factories in Bengaluru, India. These factories belong to one of the largest ready-made garment manufacturers in the world. Production in these factories takes place as follows. The firm receives orders for export production from large international buyers, and these are allocated by the marketing department of each production division (i.e., Ladies', Men's, Knits) to the factories based on capacity and regulatory compliance. Within each factory, the order is assigned to a production line based on first availability. The production line will then work on the entire order until it is ready to be prepared for shipment, usually in advance of the contracted delivery date. Each production line works on one order at a time, which usually takes between 20 to 30 days to complete.

A typical production line has around 60 workers which usually corresponds to one worker per machine. Within each line, the production process is organized in a sequence, usually grouped by segments of the garment. Between these groups are feeding points at which bundles of material for a certain number of segments are provided. For example, a group of workers assigned to machines will complete  $x$  numbers of sequential operations to produce left sleeves, another similar group will do the same for right sleeves, and another for shirt fronts with pockets, and another group will work on the collar. Completed bundles of sections of garments then feed other segments of the line, until a bundle of completed garments results at the end of the line.

Each line is managed by one line manager, whose role is to motivate workers, assign them to tasks, and ensure that production remains on schedule by identifying and relieving bottlenecks.<sup>9</sup> Importantly, workers on each line are only interacting with the line manager and *not* with the other workers on the line. So there is no team-work between workers, which limits the potential for productivity spillovers across workers.<sup>10</sup> *Line* managers are supervised by a *production* or floor

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<sup>9</sup>Managers do not move across lines so each line is identified by one line manager. Thus, we use the terms “line” and “manager” interchangeably in the paper.

<sup>10</sup>The potential for spillover effects across workers is also reduced by the fact that each worker has a buffer stock of material to work on, so that each worker’s productivity is not directly influenced by the productivity of the other workers on the line. We formally test for the presence of productivity spillovers across workers in Appendix A, and we

manager. Production managers are in charge of ensuring that their lines run smoothly and meet the delivery deadlines.

Line managers and workers are paid a fixed salary for their work, but are eligible to earn bonus pay each day that their line exceeds a minimum production threshold. The bonus is linear in productivity above this threshold and does not reflect the productivity of any other line in the factory.<sup>11</sup> Thus, managers are incentivized to utilize all available resources to maximize their output each day. Similarly, workers are also incentivized to exert effort.

There are three main stages of the production process for each garment: cutting, sewing and finishing. We focus on the sewing process for three reasons: first, it involves the majority of labor in the production process; second, it makes up the majority of the production time-line; finally, our data allow us to follow the daily composition of the team and the output of each worker/production line for the sewing process, which is needed for our analysis.

## 2.2 Data

We use three sources of data for the empirical analysis: (i) production data on worker-level productivity; (ii) production data on the orders placed by buyers; (iii) a survey of production managers that we conducted. We next describe these three datasets.

### 2.2.1 Worker-Level Productivity

The main dataset used for estimation includes daily worker-level information from the six factories, spanning over three years from March 2013 to July 2016. Over the sample period, we observe 23,608 workers distributed across the 120 production lines (and corresponding line managers) that make up the six factories. For each day of production during this period, we know the manager a worker is assigned to, the garment (or style) she is working on (e.g., man's white dress shirt of a specific brand), the operation (or task) she is assigned to perform (e.g., sewing left sleeves), and how many operations she completes. For example, if the worker is assigned to work on left sleeves at a line that produces a certain type of man's shirt, we know how many left sleeves the worker assembles on each day.

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fail to find significant evidence of any such spillovers.

<sup>11</sup>The value of the bonus ranges between 8%-10%.

For each worker, we also know the target quantity they were expected to assemble on each day. In the example of the worker assigned to left sleeves, this would be the number of left sleeves they were expected to produce per day. The target quantity is higher for less complex garments and for less complex operations on any given garment (since workers can complete more iterations of simple operations in a given day), and therefore is an appropriate way to normalize productivity across lines producing garments of different complexity, and across workers assigned to operations of different complexity. Importantly, target quantities are set at the firm level, and so are exogenous to the productivity of individual workers.<sup>12</sup>

Our measure of productivity is daily *efficiency*, which equals the percentage of the target quantity of a particular operation on a particular garment per day that is completed by the worker. This measure ranges from 0 (lowest efficiency) to 100 (highest efficiency). It is important to note that our measure of productivity is effectively quality-adjusted, as it only includes completed operations that pass specific minimum quality thresholds imposed by the firm.

In addition to data on worker-level productivity, we also have data on the daily wages of workers and managers (inclusive of the bonus) over the sample period. As described in more detail in the next section, this allows us to compare how the results of the estimation procedure to recover the sorting pattern of workers to managers differ when using wages and when using productivity as outcomes.

## 2.2.2 Orders Placed by International Buyers

We also have available a dataset with information on buyers of the garment firm. The dataset covers the period from 2012 to 2015, and includes information on all orders placed with the firm, with a corresponding unique buyer identifier. We also know when the relationship with each buyer was started (i.e. when they placed their first order with the firm). 113 different buyers placed an order with the firm over the period covered by our buyer data. This confirms that the firm we work with is a very large supplier, with many active buyers. The median buyer placed 96 separate orders with

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<sup>12</sup>The target quantity for a given garment is calculated using a measure of garment complexity called the standard allowable minute (SAM). SAM is taken from a standardized global database of garment industrial engineering that includes information on the universe of garment styles. It measures the number of minutes that a particular garment should take to produce. This number, say 30 minutes, is then broken down into the number of minutes each operation would take. If 60 operations are required to fully construct a given shirt style with a total SAM of 30, each operation would have a SAM of half a minute on average, with some operations being more complex and taking longer and others expected to take less time.

the firm over this time period, which shows that there are repeated interactions with the typical buyer. However, there is substantial variation in the importance of different buyers: buyers at the 75<sup>th</sup> (90<sup>th</sup>) percentile of orders placed 460 (2,341) separate orders with the firm over this period. As described in Section 4, such heterogeneity in the volume of orders placed by different buyers helps us shed light on the mechanisms behind our main results.

### **2.2.3 Survey of Production Managers**

Finally, we surveyed all production managers in the six factories in our sample at the time of the study.<sup>13</sup> The survey included all 80 such production managers across the six factories, and was designed to understand the main concerns of production managers. In particular, the survey focused on concerns related to lines falling behind with their orders, and what managers do to address such challenges. We use this data in Section 4 to provide further evidence on the mechanisms driving our main results on the sorting of workers to managers.

## **2.3 Descriptives on Worker Mobility and Productivity Dispersion**

Worker mobility across lines is very common in these factories. One main reason for this is worker absenteeism. In our context, absenteeism shocks are frequent and large. On a typical day, 13-14% of workers are absent, and so it often happens that the available workers are reassigned across lines to make sure that each line manager has enough workers and is able to complete the critical operations required to finish the order in time. In addition, as discussed in more detail in Section 4, workers can be reassigned across lines depending on the specific manpower needs and the progress of the different lines with the order, regardless of absenteeism. For example, productive workers from lines that are on track to meet their deadlines can be temporarily moved to lines that are falling behind in the timeline to deliver an order (or expected to fall behind). This creates another reason for the observed mobility. It is important to note that any worker reassignment across lines is decided by managers, so that workers do *not* have the freedom to choose at which line to work.

In Table 1, we present summary statistics from our main production dataset, at the factory level. Each factory has around 4,000 workers and 26 production lines over our sample period. The average tenure of workers in these factories is around 9 months (with the median at around 5 months).

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<sup>13</sup>The survey took place in early 2019.

The share of *movers* (i.e., workers that are observed at more than one production line during their tenure) is 54%.<sup>14</sup> Another way to measure the degree of worker mobility in the data is to compute for any given line  $X$ , the share of workers ever observed at that line over the sample period who are movers; that is, those who are observed also working at at least another line  $Y$  over the sample period. For the median line, this share is 88% of the workers. Regardless of which way we measure it, these results confirm that mobility of workers across managers in our data is very high.

Figures 1A and 1B show the distribution of the average efficiency of workers and managers, pooled across days, so that in each graph there is a single observation for each worker and for each manager. These figures reveal that there is substantial dispersion in the productivity of both workers and managers in our data.<sup>15</sup>

In the next Section, we describe the estimation approach to recover the sorting of workers to managers. We leverage both the high degree of mobility of workers and the high frequency data on worker productivity and wages.

### 3 Estimating the Sorting Pattern within the Firm

We begin the empirical analysis by estimating the sorting pattern between line managers and workers within the six factories in our data. This relies on obtaining estimates of worker and manager fixed effects, and then computing their correlation. To do so, we follow the approach in the seminal paper by Abowd et al. (1999), but using worker-level productivity data rather than wage data. This “AKM” approach is described in the next subsection, which discusses the main identifying assumptions and also highlights the advantages of using productivity data to overcome important identification concerns that the literature has raised about using the AKM approach with wage data. We then turn to presenting the results of the estimation.

#### 3.1 Methodology

We estimate the following two-way fixed effects model:

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<sup>14</sup>Table A1 in the Appendix reports the distribution of lines workers are observed at, and shows that, conditional on moving, the median worker is observed at three lines.

<sup>15</sup>Figure A1 in the Appendix shows the distribution of the average efficiency of workers, by factory.

$$\ln(y_{it}) = \theta_i + \psi_{J(i,t)} + x'_{it}\beta + \nu_{it}, \quad (1)$$

where:

$$\nu_{it} = \eta_{i,J(i,t)} + \xi_{it} + \epsilon_{it}. \quad (2)$$

The dependent variable,  $\ln(y_{it})$ , is log daily efficiency of worker  $i$  at time  $t$ ;  $\theta_i$  is a worker fixed effect;  $\psi_{J(i,t)}$  is a fixed effect for the manager (or line) the worker was matched to at time  $t$ ;  $x'_{it}$  are time-varying controls. The full set of time-varying controls includes style (or garment) fixed effects to account for variation in productivity due to complexity of the style and size of the order, as well as year, month and day of the week fixed effects, to account for common seasonality and growth in productivity across lines.<sup>16</sup> Finally, we include the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style, to account for line-specific learning and productivity growth during the production run, which has been shown by Adhvaryu et al. (2019b) to be important in this same context.

Following Card et al. (2013), we assume that the error term in the main equation,  $\nu_{it}$ , is the sum of a match-specific component,  $\eta_{i,J(i,t)}$ , a unit root component,  $\xi_{it}$ , and a transitory error,  $\epsilon_{it}$ . The term  $\eta_{i,J(i,t)}$  allows for the log-productivity of worker  $i$  to be inherently different across managers; the component  $\xi_{it}$  captures changes in the worker fixed effect over time, due for example to employer learning or human capital accumulation; the transitory error term  $\epsilon_{it}$  reflects any additional unobserved worker-level variation, for example health shocks that affect the productivity of the worker at particular times.

As discussed in Abowd et al. (2002), the manager and worker fixed effects in this model are separately identified only within “connected sets” of production lines, linked by worker moves across managers. Therefore, we estimate this equation on the largest connected set of workers and managers/lines within each of the six factories in our sample.<sup>17</sup> As described in the previous section,

<sup>16</sup>On style fixed effects, we note that these effectively control for differences in quality standards across buyers, as any given style is only produced by one buyer.

<sup>17</sup>A group of managers and workers are connected when the group comprises all the workers that have ever matched with any of the managers in the group, and all of the managers at which any of the workers have been matched during the sample period. The largest connected set in our data includes the entire sample of workers and managers within

the final estimation sample includes 23,608 workers observed at 120 production lines for a period of about three years. In total, this delivers 2,925,577 daily observations of the efficiency of a particular worker matched to a particular manager within the connected set of production lines.

We now discuss the specific identification assumptions related to the estimation of equation (1), and present a number of tests to validate these assumptions.

### 3.1.1 Identification Assumptions and Tests

In order to consistently estimate the parameters in (1) by OLS, we again follow the literature (see, for instance, Card et al. (2013)) and make the following identifying assumptions:  $E[\theta_i \nu_{it}] = 0$ ;  $E[\psi_{J(i,t)} \nu_{it}] = 0$ ; and  $E[x'_{it} \nu_{it}] = 0, \forall i, t$ . In particular, identification of the manager fixed effect requires a strong exogeneity assumption regarding the assignment of workers to managers with respect to  $\nu_{it}$ : we need the assignment of workers to managers to be conditionally mean-independent of past, present and future values of  $\nu_{it}$ . Note that this assumption allows for the possibility, for example, that better workers (i.e., workers with a higher fixed effect) are systematically more likely to move to more productive lines (i.e., to managers with a higher fixed effect), so that sorting on the fixed effects is allowed. On the other hand, this assumption rules out the possibility that workers and managers sort on the match-specific component of log-productivity, or on other transitory shocks to workers or managers. Any form of “endogenous mobility”, whereby workers and managers sort on  $\nu_{it}$ , would lead to biased and inconsistent estimates of the fixed effects.

We follow Card et al. (2013), and perform a series of tests for endogenous mobility. We begin by conducting an event study around moves to assess the extent to which moves might be systematically driven by productivity shocks or by sorting on the match-specific component of log-productivity. Specifically, we isolate movers in our data, and then rank them in terms of: (i) quartiles of the average efficiency of the production line they moved away from; and (ii) quartiles of the average efficiency of the production line they moved to. Figure 2 then plots the average weekly residual efficiency of the mover on the  $y$ -axis:<sup>18</sup> this is computed 6 to 10 days ( $Period = -2$ ) and 1 to 5

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each factory. This once again shows the high degree of worker mobility across managers in our data.

<sup>18</sup>To calculate worker-level residual efficiency we run a regression of log daily efficiency of the worker on: factory fixed effects; year, month and day of the week fixed effects; style fixed effects; tenure (days) of the worker in the data; tenure (days) of the worker on the line; finally, we include the experience of the line/manager in producing the current style in the current production run, as measured by the number of consecutive days spent producing that style. Standard errors are clustered by line/manager in this regression. We use this regression to calculate residual efficiency of each worker.



days ( $Period = -1$ ) before the move from the origin line, and 1 to 5 days ( $Period = 1$ ) and 6 to 10 days ( $Period = 2$ ) after the move to the new destination line, as reported on the  $x$ -axis.<sup>19</sup> This is plotted by quartiles of the average efficiency of the origin and destination line. To limit the amount of information on the graph, we only report moves away from either the top quartile in terms of average line efficiency (quartile 4) or the bottom quartile of average efficiency (quartile 1).

If match-specific components,  $\eta_{i,J(i,t)}$ , are important in driving moves, this means that workers are more likely to move to managers where their productivity is either particularly high, or particularly low (depending on whether there is positive or negative assortative matching on the match-specific component of productivity). If this is the case, then we would expect worker productivity to either gain on average (in case of PAM) or lose on average (in case of NAM) from moving to a new line. Instead, if moves are not driven by match-specific components, on average workers who move to higher productivity managers (i.e. to managers with higher fixed effects) will become more productive, and workers who move to lower productivity managers will become less productive. Figure 2 shows that indeed workers moving to better lines tend to gain in terms of productivity, while workers moving to worse lines tend to lose in terms of productivity. In addition, workers who move from a line in the highest quartile to a line in the highest quartile experience close to zero change in productivity, and the same is true for workers who move between lines in the lowest productivity quartile. These results are consistent with the absence of an average “premium” or an average “penalty” for movers, which supports the identification assumptions.<sup>20</sup>

To further validate that the match-specific component of productivity is not important in driving moves, we compare the Adjusted  $R^2$  from the estimation of equation (1) with the Adjusted  $R^2$  from a fully saturated model with dummies for each worker-manager combination. Table A2 in the Appendix shows that the improvement of fit from the fully saturated model is very limited

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<sup>19</sup>The sample for the graph is restricted to the balanced sample of workers continuously working at the origin line for at least 10 days prior to the move, and continuously working at the destination line for at least 10 days after the move.

<sup>20</sup>As discussed in Card et al. (2013), if the moves are conditionally mean independent of the match-specific component, then the gains from moving from manager  $X$  to manager  $Y$  should be equal and opposite to the losses from moving from manager  $Y$  to manager  $X$ . That is, gains and losses for movers should be symmetric. A full symmetry test across all potential combinations of origin and destination lines (ranked by quartiles of average line efficiency) is reported in Figure A2 in the Appendix. The Figure again shows that moving to a higher productivity manager results in a gain in productivity, while moving down results in a loss in productivity, with the exception of moves from the third to the second quartile, and moves from the fourth to the third quartile of lines, as these are associated with small increases in productivity despite being a move down. The Figure further reveals that the gains from moves up and the losses from moves down are relatively symmetric. While we do observe some deviations from the 45 degree line, these deviations do not appear to have a systematic direction, which is reassuring.

(the Adjusted  $R^2$  increases by only .017 when going from column 4 to column 5). This shows that match-specific components play a very minor role in explaining variation in productivity, so that any scope for sorting on such components is limited. Finally, in Figure A3 in the Appendix, we report the average residuals from the estimation of (1), by quartiles of the estimated worker and manager fixed effects. The average residuals are very small for all groups (substantially below 1% in absolute value in all cases). This is again consistent with match effects not being quantitatively important, and so provides further support to the additive log-separability assumption of equation (1).

A second concern about  $\xi_{it}$  arises if those workers who are on a particularly positive productivity trend at a given line are more likely to move up, and those who are performing particularly badly are more likely to move down, as this would lead to an overestimate of the manager effect for high-type managers, and to an underestimate for low-type managers.<sup>21</sup> We check whether the productivity of movers at the origin line exhibits systematic trends in the days just before the move: while Figure 2 reveals that worker residual productivity does exhibit some movement in the periods before the move, these do not seem to be systematically related to whether the worker then moves to a higher productivity or a lower productivity manager, which again supports the assumption of conditional exogenous mobility.<sup>22</sup>

Third, suppose that workers who experience a positive transitory productivity shock  $\epsilon_{it}$  are systematically more likely to move up to more productive lines: since the shock is transitory, this would lead to an underestimation of the manager fixed effect, due to mean reversion.<sup>23</sup> Again, as shown in Figure 2, the absence of systematic trends before (or after) the move takes place helps alleviate such concerns.<sup>24</sup>

Taken together, the evidence from this section provides support to the identification assumptions detailed above: while mobility in our data is high, such mobility does not seem to be driven by match-

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<sup>21</sup>A similar concern arises if workers who are performing particularly well are systematically more likely to move down, and those with negative trends are more likely to move up. This would result in overestimating the manager effect for low-type managers, and underestimating the manager effect for high-type managers.

<sup>22</sup>We further validate this in Table A3 in the Appendix, which studies whether changes in average residual productivity in the two weeks before the move systematically predict the direction of the move. In line with Figure 2, we find no significant evidence of changes in productivity predicting where workers move.

<sup>23</sup>If workers who experience negative productivity shocks are more likely to move up, this would instead result in an overestimate of the manager effect, again due to mean reversion.

<sup>24</sup>The results in Table A3 in the Appendix provide further support to this conclusion, as we fail to document a significant correlation between fluctuations in productivity in the two weeks before the move and the direction of the move.

specific components of log-productivity, or other unobserved time-varying worker components.<sup>25</sup>

### 3.1.2 Addressing Limited Mobility Bias

Another concern with the estimation of (1) is the so-called “limited mobility bias” (Abowd et al., 2004; Andrews et al., 2008, 2012). As discussed above, identification of the worker and manager fixed effects requires: (i) observing a worker at multiple managers; (ii) observing a manager with multiple movers. If in practice the number of moves is limited and the size of each line is small, then this can bias the correlation between the estimated worker and manager fixed effects, and the bias will be negative. Intuitively, if the presence of limited mobility does not allow to separately identify the worker and manager fixed effects, then if the worker effect is overestimated, the manager effect will be underestimated, and vice versa, creating negative bias in the correlation of the estimated worker and manager fixed effects.

We address limited mobility bias in two ways. First, we note that in our data: (i) mobility is much higher than in typical matched employer-employee (MEE) datasets; and (ii) lines are much larger than the average firm in typical MEE datasets. As shown in Table 1, more than 50% of workers in our sample move at least once, and the average line has around 60 workers at each point in time. By contrast, the share of movers in most related across-firm studies is much lower. For instance, the share of workers who move at least once across firms is around 12% in the German data in Andrews et al. (2012), and about 35% in the Brazilian data in Alvarez et al. (2018).<sup>26</sup> Also, the simulations in Andrews et al. (2008) are conducted only for firm sizes of at most 15 employees. These considerations already limit concerns related to limited mobility bias in our setting. To further alleviate concerns related to limited mobility bias, we perform the bias correction procedure suggested by Andrews et al. (2008),<sup>27</sup> which is standard in the literature, as well the latest covariance

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<sup>25</sup>One final note on identification concerns the use of style fixed effects. The model in equation (1) can effectively be seen as a three-way fixed effect model with worker, manager and style effects. Separately identifying the style and manager effects requires a strict exogeneity assumption on the assignment of styles to managers. As described in Adhvaryu et al. (2019b), any scope to assign styles to managers based on comparative advantage is limited in practice by difficulties in forecasting the arrival and timing of orders, and by the high opportunity cost of leaving lines idle while waiting for new orders to arrive. Consistently with this, Adhvaryu et al. (2019b) find no evidence that lines are left idle, and the number of lines completing or starting an order on the same day is rarely more than one, indicating that the possibility of reallocating orders across managers is quite limited in practice. This evidence all supports the validity of the strict exogeneity assumption in the allocation of styles to managers in this context.

<sup>26</sup>The degree of worker mobility in our data is more similar to the one in related studies leveraging data on the assignment of workers to managers within the firm, such as Lazear et al. (2015) and Hoffman and Tadelis (2019).

<sup>27</sup>Andrews et al. (2008) show that the estimated correlation between worker and firm fixed effects is biased downward if there is true positive assortative matching and any covariates are uncorrelated with the firm and worker fixed

shrinkage methods proposed by Best et al. (2019).<sup>28</sup> In line with limited mobility bias not being substantial in our setting, we show that our key findings are robust to both types of corrections.

### 3.1.3 The Advantage of Productivity Data

Before turning to the results, we note that a key advantage of our data is that it includes information on job-level productivity. This allows us to overcome a long-standing concern in the literature that wage data is inappropriate to recover the sign of sorting. In particular, Eeckhout and Kircher (2011) highlight that in the presence of a positive cross-partial derivative in production between worker and manager types, wages (in levels) can be non-monotonic around the optimal allocation. This causes the firm fixed effect estimated from wage data to be uncorrelated with the underlying firm type, thus preventing identification of sorting with wage data. We are able to overcome their critique because even in the presence of a positive cross-partial, worker productivity will be monotonic in the line (or manager) type, which justifies using the AKM framework with productivity data. To further highlight the importance of using productivity data, we contrast our results using productivity data with those using wage data below.

## 3.2 Results

We estimate equation (1) by OLS. Table 2 reports the results of the estimation, averaged across the six factories in our data. Column 1a and 1b focus on our baseline AKM model, which includes style fixed effects; year, month and day of the week fixed effects; and the number of consecutive days that the line has been producing a given style at time  $t$ , to account for learning (Adhvaryu et al., 2019b). The key parameter of interest is the correlation between the worker and the manager effects,  $Corr(\theta_i, \psi_j)$ . Column 1a shows that this is estimated to be *negative* and relatively large

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effects. This correlation becomes more negative as the number of movers decreases, and as such they refer to this issue as limited mobility bias. They propose a bias correction estimation procedure and show that the bias corrected correlation is approximately unbiased. We implement this same correction procedure.

<sup>28</sup>Best et al. (2019) extend standard shrinkage methods (e.g. Kane and Staiger (2008), Chetty et al. (2014)) to explicitly account for the correlation between the estimation error of the two vectors of fixed effects (in their case bureaucrat and organization fixed effects). We use bootstrap estimation to construct the variance of our manager and worker fixed effects. To account for the covariance of the estimation errors of the manager and workers fixed effects, we follow the shrinkage approach proposed by Best et al. (2019): let  $\hat{\Theta}$  be a vector with the estimated worker and manager fixed effects. Then, the shrinkage matrix  $\Lambda^*$  is defined as  $\arg \min_{\Lambda} \mathbf{E} \left[ \left( \Theta - \Lambda \hat{\Theta} \right) \left( \Theta - \Lambda \hat{\Theta} \right)' \right]$ . That is, we find the weights  $\Lambda$  that minimize the expected mean squared error of the prediction of the linear combination of worker and manager fixed effects. We then “shrink” the estimated worker and manager fixed effects by multiplying them by such weights.

at around  $-16\%$ . Column 1b reports bootstrap standard errors, and shows that the correlation between the worker and manager effects is highly significant at the 1% level.<sup>29</sup> These results indicate that on average higher-productivity workers are more likely to be matched with lower-productivity managers.

In columns 2-6 we perform a series of robustness checks on our negative assortative matching result. First, to check sensitivity to the inclusion of control variables, we additionally control for both worker tenure in the data and worker tenure on the line, measured respectively as the number of work-days since the worker is observed in the data the first time, and the number of work-days since she started work on the line she is currently observed at at time  $t$ .<sup>30</sup> Second, we add a fixed effect for every day in the data, in order to account for potential daily shocks to productivity. Third, to correct for sampling error in the estimation of the key correlation of interest, we implement a split-sample approach (Best et al., 2019; Finkelstein et al., 2016).<sup>31</sup> Finally, to address limited mobility bias, we implement the Andrews et al. (2008) bias correction and the Best et al. (2019) covariance shrinkage procedure described above. The results in columns 2-6 of Table 2 show that the estimated correlation between worker and manager fixed effects is largely unaffected by these robustness checks, and always remains negative, between  $-0.11$  and  $-0.22$ . The robustness of our estimation results is consistent with the high degree of worker mobility in this setting and the large sample size, which likely reduce limited mobility bias and sampling error.

In Table 3, we compare the results of the estimation of equation (1) from our baseline model: (i) when using productivity (column 1) and (ii) when using wages as outcomes (column 2). Column 2 shows that when wages are used, the estimation returns a correlation very close to zero. This is in line with the discussion in Eeckhout and Kircher (2011) that the firm fixed effect estimated with wage data is usually uncorrelated with the true firm type, thus potentially leading to a correlation of zero between the worker and the firm fixed effect. Further, the lack of correlation between the worker and manager fixed effects when using wage data may also reflect at least in part the limited

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<sup>29</sup>We follow Best et al. (2019) to construct our bootstrap standard errors. We construct residuals and randomly resample the residuals, stratifying by manager-worker pair to preserve the match structure of the observations. We then re-estimate the line and worker fixed effects. We repeat this procedure 100 times, and use the distribution of the estimates to compute standard errors.

<sup>30</sup>We do not control for worker tenure in the factory as we have incomplete data on this variable.

<sup>31</sup>We randomly split our sample in half, stratifying by manager-worker pair. We then estimate equation (1) by OLS separately on each sample. We compute each statistic presented in Table 2 for each sample and then take the average across the two samples.

wage variation in the data, driven by the nature of wage setting in these factories, where the largest component of worker wages is a fixed salary. This again highlights the importance of using data on productivity in the estimation of sorting within the firm.

We further verify the results in Table 2 by studying the direction of moves in our data: the negative documented correlation between the worker and manager fixed effects implies that the most common moves should involve a high productivity worker moving to a low productivity manager, and a low productivity worker moving to a high productivity manager. On the other hand, moves of high productivity workers to high productivity managers, as well as low productivity workers to low productivity managers, should be less frequent. Table 4 presents descriptive evidence on the pattern of worker moves across managers. To do so, we divide both workers and managers into those with an estimated fixed effect in the top quartile (“High” type) and those with a fixed effect in the bottom quartile (“Low” type) over the sample period. We then report the daily probability of observing a worker of a given type moving to a manager of a given type. The results show that the likelihood of a high type worker moving to a low type manager is indeed almost four times as large as the likelihood of a high type worker moving to a high type manager (0.75% vs 0.19%). Also, low type workers tend to move more often to high type managers than to low type managers (0.88% vs 0.56%). This pattern of moves is consistent with the negative sorting results in Table 2. While the estimated fixed effect of the worker predicts the *direction* of moves, it does not predict the likelihood of a move occurring. To show this, in Figure A4 in the Appendix we report the frequency of moves by whether the worker has an estimated fixed effect above or below the median. The figure shows that the two distributions are almost perfectly overlapping. This limits concerns that the high degree of mobility in the data is generated by a few highly productive “floaters” workers moving very often across lines.<sup>32</sup>

Next, we explore the robustness of this negative sorting result across different groups of workers. Table 5 shows that our results are not driven by some particular groups of workers, and instead hold for both high and low skilled workers, and for high and low paid workers. Also, Table 5 shows

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<sup>32</sup>On worker mobility across managers we further note that the majority of moves take place just at the start of a new order (22% of all moves in the data take place on the first day of production of a new order, and 57% within the first seven days). This is consistent with the strong learning effects documented in this context by Adhvaryu et al. (2019b): much of the learning on a new style takes place in the first days of the production run, which then makes it more costly for the firm to move workers across lines later on in the production run (as movers need to get up to speed with the rest of the production line).

that the result holds both when workers are observed at their primary or “home” line, and when they are observed at other lines. In addition, the table shows that the results are very similar when they are estimated on the sample of movers only, which again reassures us that limited mobility bias is not substantial in our data.

Figure A5 in the Appendix reports the estimated correlations between worker and manager effects by factory. These are negative for five of the six factories, and the other correlation is very close to zero, thus suggesting that the negative sorting pattern estimated on average is reflective of the organization of production across most of the factories. As Figure A5 highlights however, there is substantial heterogeneity in the magnitude of sorting across factories. We return to explaining this heterogeneity in the next section.<sup>33</sup>

## 4 Drivers of Negative Assortative Matching

The results from the previous section uncover the presence of negative assortative matching between workers and managers within the firm. This means that on average, high productivity workers are more likely to be observed at production lines with low productivity. The key question that emerges then is what is causing this sorting pattern: is this driven by the shape of the production function, so that higher ability workers are more productive when matched to lower productivity managers? Or does this reflect some other underlying constraint in production, so that even though it might otherwise be optimal to match high productivity managers with high productivity workers, some other “force” pushes the allocation towards NAM? In this section, we examine potential drivers of the observed sorting pattern. Understanding this is important to shed light on the constraints firms face in the production process, and how these affect firms’ ability to exploit the underlying production technology between workers and managers in their production decisions.

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<sup>33</sup>In the estimation of the manager and worker fixed effects we are abstracting from the size of the production line, in terms of number of workers assigned to the line on any given day. We do so because there is limited variation in the size of each line both across managers and across days within managers. To see this, in Table A4 we regress the number of workers assigned to the manager/line on any given day on: (i) the fixed effect of the manager and (ii) the number of days since the start of the order. The data set is at the line-day level. We find that neither of these regressors are significant predictors of the length of the line.

## 4.1 The Role of the Underlying Production Technology

We begin by examining the potential role of the shape of the production function in driving the observed allocation: if the production function had a negative cross-partial between manager and worker types, then this would explain the observed sorting pattern, as NAM is the allocation that maximizes output given that technology. On the other hand, if there is a positive cross-partial between manager and worker types, then this indicates that the optimal unconstrained allocation should exhibit PAM, and so the firm must face other constraints that push towards NAM, potentially making NAM the constrained efficient allocation.

We note that equation (1) is effectively a production function in logs, since the outcome is a normalized measure of output. In the previous section, we have assumed that this equation is additively separable in the worker and manager fixed effects. This is equivalent to assuming that the production function, in levels, exhibits a positive cross-partial between worker and line type (i.e., that worker and manager effects enter multiplicatively in levels). For instance, equation (1) is consistent with the underlying production function being Cobb-Douglas in levels. As long as the identification assumptions laid out in the previous section are satisfied, then this implies that productivity would be maximized by implementing a *positive* assortative matching allocation.

The identification tests conducted in the previous section support the assumption of additive separability in logs. In particular, the fact that the Adjusted  $R^2$  from the estimation of equation (1) does not increase substantially once match effects are included (Appendix Table A2), and that the average residuals are small (Appendix Figure A3) suggests that match effects are not important in logs. This is in line with a zero cross-partial in the log form of the production function. In turn, then this implies a positive cross-partial in levels.

To further explore the shape of the underlying production technology, Appendix A describes an alternative production function estimation procedure that we undertake. This does not rely on the estimation of worker and manager fixed effects, and so is complementary to the estimation of equation (1). In short, the procedure amounts to splitting the sample into two periods: in the first period (e.g., the first three months of data), we rank workers and managers by deciles of their raw average daily efficiency. This determines the worker and manager “types”. We then use these as inputs for estimating the production function in the second period by OLS. The results again



confirm that we cannot reject that the production function is additively separable in logs.

Taken together, this evidence shows that we cannot reject that the underlying production function is Cobb-Douglas between worker and manager types. Since the cross-partial of the Cobb-Douglas is positive in levels, this means that the output of a given worker is *increasing* in the manager type. This is in line with much of the literature on managerial incentives, which tends to assume complementarities between managers and workers, and more generally between inputs in the production process.<sup>34</sup>

Given this underlying technology, we would then expect to find positive assortative matching as that would lead to output maximization. In line with this, as discussed in more detail in Section 5 below, we show that productivity would increase significantly in these factories under a counterfactual allocation that implements the positive assortative matching assignment. The shape of the underlying production function cannot be the driver of the observed allocation then, and so there must be other constraints that create an incentive for the firm to deviate from the positive assortative matching allocation, potentially making the negative assortative matching allocation the constrained efficient one. We turn to this in the next sub-section.

## 4.2 The Role of Supply Chain Constraints

As discussed by the theoretical literature on sorting in the labor market, the presence of a positive cross-partial in production typically leads to PAM in a competitive equilibrium in which production units compete with each other (Eeckhout, 2018). However, even in the presence of complementarities, NAM can emerge if there is a social planner that internalizes the externalities imposed by the more productive teams to the less productive ones. In our context, this would be the case if the central management of the firm cares about *all* teams meeting a certain minimum level of productivity. That is, if there is a large penalty (in terms of profits) associated with having a production line fall behind on a given order, then this might result in the central management finding it optimal to pair more productive workers with less productive managers. This would then lead to NAM, even if the underlying production technology would push towards PAM.

As described above, our partner firm is a supplier to large international buyers. In this context,

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<sup>34</sup>For example, Bandiera et al. (2007) and Bandiera et al. (2009) consider complementarities between managerial and worker effort; Amodio and Martinez-Carrasco (2018) find evidence in favor of complementarities between worker quality and input quality.

meeting production deadlines with buyers can be a possible motive for the observed negative assortative matching, since missing a deadline on any given order can harm future contracts or even lead to the termination of the relationship altogether. We next provide direct evidence on this channel, using both a survey of production managers that we conducted, as well as data on the orders placed by international buyers.

#### 4.2.1 Evidence from a Survey of Production Managers

As described in Section 2, we surveyed all production managers in the six factories in our sample, asking them about their main concerns in production. Each production manager supervises multiple lines, and they are responsible for the productivity and progress toward order completion of all the lines under their control. Specifically, we asked managers to indicate the relative importance of four potential concerns in their operations: (i) lines not meeting their target/running slow; (ii) worker absenteeism; (iii) line manager absenteeism and (iv) customers not paying for their orders on time. Managers were asked to use a 1 to 5 scale to indicate the importance of each concern, with 1 meaning “not worried at all”, and 5 meaning “very worried”. Figure 3 shows that difficulties in meeting targets are reported as the most important concern, together with concerns about customers not paying on time for their orders. Interestingly, Figure 3 shows that concerns related to lines falling behind are even more important than concerns related to worker or manager absenteeism.

To understand why production managers are concerned about lines falling behind, we asked them what are the consequences for the firm if a production line is slow and does not meet the deadline for a given order. We report answers to these questions in Panel A of Table 6, which shows that: 51% of production managers say that there would be substantial monetary losses for the firm from being late even with a single order, and 33% report that the firm might lose the customer altogether from being late with the order. In line with this being a problem for production managers, the survey further reveals that 19% of managers have experienced delays with a production line under their supervision.

We then asked managers about the strategies they adopt to try and avoid having lines fall behind. As shown in Panel B of Table 6, 91% of managers would consider moving workers across lines to help the low-performing lines catch up. Importantly, we asked which *types* of workers they would be more likely to shift from a highly productive line to a lower productivity line, and in 97%

of cases managers would move the *most* productive workers to the *least* performing line. This is exactly the pattern of moves that would generate negative assortative matching.

As discussed in Section 3, Figure A5 shows that there is significant heterogeneity in our estimates of the correlation between worker and manager fixed effects across the six factories in our data. In Figure 4, we then check whether the degree of NAM is stronger in those factories where managers on average are more concerned about lines falling behind and not meeting deadlines for their orders with buyers. The Figure plots the estimated degree of NAM in each factory against the relative reported concern of managers about lines not meeting deadlines.<sup>35</sup> While the pattern depicted in this Figure is merely suggestive given the small number of factories, indeed we find stronger NAM in those factories where managers are more concerned about lines not meeting their targets.

Taken together, the evidence from this survey is consistent with constraints related to the structure of supply chains pushing the firm towards implementing negative assortative matching. That is, missing the deadline for an order is costly for the firm, and so production managers reallocate high productivity workers to low productivity lines, to make sure that lines do not fall behind.

#### 4.2.2 Evidence from the Orders Placed by International Buyers

A related literature on supply chains in developing countries highlights the value for suppliers of long-term relationships with large buyers (Cajal Grossi et al., 2019; Macchiavello and Morjaria, 2015). We can then expect the firm to place more weight on safeguarding relationships with established and large-volume buyers, as these are relationships that are particularly valuable to the firm. If this is the case, we would then expect to find a higher degree of NAM on those orders placed by the largest buyers.

To explore this hypothesis, we leverage the buyer dataset described in Section 2. This dataset includes information on all orders placed with the firm from 2012 to 2015, with a corresponding unique buyer identifier. To identify “Large” buyers we create a dummy equal to one if the buyer is in the top decile of the total number of orders placed with the firm in the period covered by our buyer data. We then compute the correlation between worker and manager fixed effects from the

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<sup>35</sup>For each factory, we divide the average reported concern about lines not meeting deadlines by the factory average of all concerns managers were asked about. We then plot this on the  $y$ -axis of Figure 4.

estimation of (1), separately for orders placed by Large buyers and orders placed by other smaller buyers.<sup>36</sup> Table 7 reports the results, and shows that indeed NAM is largest on those orders placed by the largest buyers: the estimated correlation between worker and manager effects is  $-.173$  for buyers in the top decile of orders, and is  $-.117$  for other buyers.

Finally, we study how the degree of NAM between workers and managers has evolved over our sample period. The literature on relational contracting has highlighted that as the reliability of a supplier is proven, this lowers the incentives of the supplier to engage in costly actions to signal its reliability to the buyer over time (Macchiavello and Morjaria, 2015). In our context, this would translate into the degree of NAM becoming less strong over time, as the firm establishes its reputation with buyers. For instance, the buyer might become less strict in enforcing deadlines as reputation is developed. Figure 5 shows the evolution of the correlation between worker and manager fixed effects by semester and by whether the orders were placed by “Large” or “Small” buyers, where Large buyers are defined as those in the top decile of the total number of orders placed in our sample period (the same definition as in Table 7).<sup>37</sup> The figure reveals two key findings. First, the degree of NAM on orders placed by smaller buyers is always lower than on orders placed by larger buyers throughout our sample period, which is in line with the results in Table 7. Second, the correlations between worker and manager fixed effects become gradually less strong over time, and approach zero towards the end of our sample period. This is true for all types of buyers. This significant trend is in line with the results of Macchiavello and Morjaria (2015) and indicates that as the relationship lengthens and reputation is established, the distortion in the internal allocation of labor is reduced.<sup>38</sup>

These results reinforce the claim that constraints related to the nature of supply chains with large buyers provide an incentive for the firm to implement negative assortative matching. Doing so

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<sup>36</sup>Buyers in the top decile placed 66% of all orders over the period covered by our data.

<sup>37</sup>To generate the correlations reported in Figure 5 we estimate equation (1) on the full sample used to produce the results in Table 2, but then report the correlations of interest only over those semesters for which we have a balanced sample of factories and lines. Doing so ensures that any changes in the correlations over time are not driven by sample selection.

<sup>38</sup>Macchiavello and Morjaria (2015) show that the willingness of suppliers to engage in costly actions to signal reliability exhibits an inverted-U shape over time, as both the value of relationships and reputation increase over time (so that young relationships are not as valuable, and old relationships do not require as many costly signals to be maintained). The relationship between our partner firm and the median buyer was established in 2010, that is a few years before the start of our sample period. This might explain why we find a monotonic relationship instead of a U shape in the degree of NAM over time: relationships are on average well established by the time our data begins, and this might then prevent us from picking up those early time periods in the relationship when NAM should become larger over time as the relationship becomes more valuable (but reputation has not been established yet).

might be optimal for the firm in terms of profits, given the constraints faced. However, the results of our production function estimation suggest that output and productivity would be higher in a counterfactual scenario in which the firm was not facing such supply chain constraints, and could instead afford to keep some highly productive lines and some less productive lines. These results highlight that constraints related to the structure of supply chains limit in important ways the productivity of the firm. We expand on this point in the next section, where we quantify the loss in productivity related to implementing the observed negative assortative matching allocation.<sup>39</sup>

## 5 Productivity Gains from Labor Reallocation

The analysis in the previous section shows that supply chain constraints push the firm towards implementing negative assortative matching. This is likely the allocation that maximizes profits given the supply chain constraints faced by the firm, but is not the allocation that would maximize productivity in an unconstrained environment. In this section, we quantify the loss in productivity that is associated with implementing the current allocation. This sheds light on the size of the supply chain constraint, that is, on how much the firm is willing to sacrifice in terms of productivity in order to safeguard its relationship with important buyers.

To quantify the productivity gains from labor reallocation, we simulate total firm efficiency under a perfect positive assortative matching allocation. The simulation is implemented as follows. We randomly extract one day from the sample period, and for that day we record: (i) the observed allocation of workers to manager/lines and (ii) the fixed effects of the workers and managers (that are estimated from equation (1) run on the full sample). We then artificially move workers across managers to implement the perfect positive assortative matching allocation. This corresponds to assigning the workers with the highest fixed effects to the managers with the highest fixed effects and so on, respecting the line sizes observed in the data. Individual worker efficiency is then predicted using the estimated equation (1), but with workers and managers matched following perfect positive assortative matching. The predicted log efficiency from (1) is then exponentiated to recover the

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<sup>39</sup>The documented heterogeneity in NAM by Large and Small buyers suggests that suppliers might face a trade-off when deciding which buyers to match with: relationships with larger buyers are potentially more valuable as these buyers place more orders, but this comes at the expenses of a larger distortion in the allocation of labor (in order to make sure that such important deadlines are met). Providing more evidence on how these considerations affect the endogenous matching of buyers with suppliers in global supply chains remains an important topic for future research.

counterfactual efficiency in levels, which is then summed across all workers and all managers. This procedure is then repeated on 1,000 randomly extracted days.

Figure 6 reports the estimated productivity gains from the counterfactual simulation, across the six factories in our data. We plot the mean increase in daily efficiency under positive assortative matching, together with confidence intervals, where bootstrap standard errors are used to construct the confidence interval. The figure shows that the productivity gains from reallocation are in the range 1-4%. As expected, the gains are larger for those factories where NAM is also larger, as these are the factories that have more scope for gains from reallocation.<sup>40</sup>

The magnitudes in Figure 6 give a sense of the “value” of this supply chain constraint for the firm. That is, they show that the firm is willing to sacrifice between 1-4% of productivity in order to avoid delays in meeting deadlines with buyers. This is a sizable reduction in productivity, which is in line with such relationships being valuable for the firm in terms of profits. Recent literature has focused on the value of repeated relationships with large buyers (Cajal Grossi et al., 2019; Macchiavello and Morjaria, 2015). Our results contribute to this literature by showing that in order to safeguard such valuable relationships, the firm is willing to “misallocate” labor internally, thus giving up some productivity. This result provides new insights into how supply chain constraints determine firm productivity.<sup>41</sup>

## 6 Conclusion

We characterize the pattern of assortative matching between workers and managers in the context of a large readymade garment manufacturer in India. We extend the across-firm sorting literature by estimating the sorting pattern *within* the firm, and by leveraging granular data on *productivity* rather than wages. We find evidence of negative assortative matching (NAM) – that is, better managers tend to match with the worse workers, and vice versa. However, our results also show that the current allocation is not the one that maximizes productivity: we show that the underlying

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<sup>40</sup>Note that the relationship between the gains from reallocation and the estimated NAM does not have to be monotonic necessarily. This is because the potential for each factory to gain from reallocation depends not only on the degree of NAM, but also on the distributions of the worker and manager fixed effects, which are likely to vary by factory.

<sup>41</sup>In Figure A6 we report the results of a simulation that is exactly the same as the one described above, but where we implement the random matching allocation instead of the perfect positive sorting allocation. As expected, the gains from labor reallocation are lower in this case but still positive, since random sorting still creates an improvement in productivity relative to the negative sorting allocation observed in the data.

production technology exhibits a positive cross-partial derivative between manager and worker types, which implies that productivity would be maximized by implementing positive sorting instead.

Together, these two facts emphasize another channel through which managerial quality may contribute to low productivity in developing country settings (Bloom and Van Reenen, 2007; McKenzie and Woodruff, 2016). That is, not only is the stock of managerial skill low, but the existing stock may not be properly allocated to maximize productivity. This discrepancy also emphasizes the distinction between empirical estimates of sorting and the shape of the underlying production function (Eeckhout and Kircher, 2011).

We note that if the firm instead were able to positively sort, aggregate output would increase by between 1-4% across the factories in our data. We hypothesize that negative matching arises, despite this loss in productivity, because of strong incentives to avoid long delays in completing any particular order. That is, the firm is willing to forfeit some productivity to ensure that minimum productivity on least productive lines does not fall so low as to delay completion and delivery of an order. We conduct a survey of managers to assess the importance of these considerations and find that factories in which managers are most worried about falling behind on orders are indeed the ones where negative sorting is strongest. In addition, the negative sorting is strongest on orders placed by the largest buyers. Relationships with these buyers are particularly important to the firm, and so this provides further evidence that the negative sorting is driven by incentives to avoid delays on deadlines with important buyers.

Our results suggest that the presence of underlying constraints related to the nature of supply chains (i.e., the risk of damaging valuable relationships with buyers) prevents firms from fully exploiting the underlying production technology. These results contribute generalizable insights to the study of the large gap in productivity between developed and developing country firms (Caselli, 2005; Hall and Jones, 1999) and the impact of trade relationships on closing or widening this gap (Atkin et al., 2017). Our results indicate that suppliers to the global market, concentrated in developing countries, may be beholden to a small set of powerful buyers from developed countries, and may be driven, as a result, to “misallocate” managerial skill in service of these relationships, even at the expense of productivity. This stands in contrast to recent evidence of learning-by-exporting, in that we document one way in which buyer relationships might actually *reduce* supplier productivity.

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## Appendix A: Production Function Estimation

In this Section we perform a simple alternative production function estimation procedure, which sheds light on the role of the underlying production technology.

Our procedure exploits the fact that we have a long panel of workers and production lines (and corresponding line managers), observed daily for three years. In particular, to get a measure of underlying worker and manager productivity or “type”, for each worker and each manager we calculate their average productivity over the first three months in which they are observed in the data. To do this, we use all workers and production lines in our data. We maintain a strict exogeneity assumption in the allocation of workers to managers, which in the context of production function estimation is in line with the approach of Graham et al. (2014, 2018). Under this assumption, and as long as there is enough mobility of workers across managers, this approach allows to recover an underlying measure of worker and manager productivity in the first three months of data. As shown in Table 1, the share of movers is high at more than 50% in our data, which is reassuring. We then rank workers and managers into quartiles of this baseline measure of productivity, and estimate a production function using *only* the later time periods, i.e. excluding the first three months of data. So effectively we calculate the worker and manager types in the first three months of data, and then use these to estimate the production function in the later time periods.<sup>42</sup> For robustness, we also repeat this procedure calculating worker and manager underlying productivity in the first four months of data (rather than the first three months).

Specifically, we estimate the following linear in logs model:

$$\ln(y_{it}) = \beta_0 + \beta_1 WorkerQ_i + \beta_2 ManagerQ_{J(i,t)} + \beta_3 WorkerQ_i \times ManagerQ_{J(i,t)} + x'_{it}\delta + \epsilon_{it} \quad (3)$$

where  $\ln(y_{it})$  is the log daily efficiency of worker  $i$  on day  $t$ ;  $WorkerQ_i$  is the quartile of average productivity of worker  $i$  as measured in the first three months of data (so note that this is not time-varying in the second period);  $ManagerQ_{J(i,t)}$  is the quartile of the average productivity of manager  $j$  where worker  $i$  is matched at time  $t$  (again estimated in the first three months only);

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<sup>42</sup>Our choice to compute the manager and worker average productivity using the first three months of data reflects the fact that average tenure for workers in the sample is around nine months. So by using the first three months to estimate the worker type, we still have available about six months for the actual production function estimation.

finally,  $x'_{it}$  are time-varying controls.<sup>43</sup>

Equation (3) is an approximation to a Constant Elasticity of Substitution (CES) production function in logs. We expect positive estimates of  $\beta_1$  and  $\beta_2$  as we expect the output to increase in both worker and manager types. The coefficient  $\beta_3$  on the interaction instead corresponds to the cross-partial in the log-form of the CES. Therefore, a negative coefficient on the interaction would imply a negative cross-partial in levels; a coefficient of zero would be consistent with the underlying production function being Cobb-Douglas, and so with a positive cross-partial in levels; and a positive coefficient would again imply a positive cross-partial in levels and complementarity in production. We estimate regressions like these by OLS, clustering standard errors at the manager/line level.

Appendix Table A5 reports the results: as expected, we find positive and significant estimates of both  $\beta_1$  and  $\beta_2$ . For instance, looking at columns 1 and 2, we see that an increase of one quartile in manager productivity is associated with a 1.7-1.8% increase in worker productivity. In addition, we cannot reject that the interaction term is *zero*: the estimates of the interaction terms are very small in magnitudes, and not significant. Therefore, we cannot reject that the underlying production function is Cobb-Douglas. Since the cross-partial of the Cobb-Douglas is positive in levels, this means that the output of a given worker is increasing in the manager type. Table A5 further shows that the results are very similar whether we use the first three months (columns 1 and 2) or the first four months of data (columns 3 and 4) to calculate the worker and manager types in the initial period.

In sum, the results of this simple production function estimation procedure again confirm that we find a positive cross-partial in levels between managers and workers, so that the productivity of a given worker *increases* in the manager type.<sup>44</sup>

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<sup>43</sup>These include style (or garment) fixed effects to account for variation in productivity due to complexity of the style and size of the order, as well as year, month and day of the week fixed effects, to account for common seasonality and growth in productivity across lines.

<sup>44</sup>As discussed in Section 2, the nature of work in these production lines is such that there is no direct interaction between workers in the production process. Also, each worker has a buffer stock of material to work at. This limits the potential for complementarities or substitutabilities across workers. The literature however has pointed out the potential importance of peer pressure or social motives in creating spillover effects on productivity across workers even when the production technology does not feature teamwork (Bandiera et al., 2010; Ichino and Maggi, 2000; Moretti and Mas, 2009). We formally check for the presence of spillover effects across workers in Table A6 in the Appendix, where we add to regressions like (3) the share of workers in the highest quartile of productivity working at line  $j$  at the same time as worker  $i$ . Reassuringly, we find that the coefficient on this variable is not significant, which again suggests that production is separable across workers and any spillover effects across productivity groups are limited in our context. We note however that the standard error on the estimates of the effect of the share of workers in the highest quartile is sizeable.

## Tables and Figures

Table 1: Summary Statistics

Factory (1)	N. Observations (2)	N. Workers (3)	N. Movers (4)	N. Lines (5)
1	742,221	5,001	2,464	29
2	573,855	4,743	2,660	16
3	595,409	4,504	2,239	26
4	311,961	2,702	1,673	8
5	292,077	2,699	1,659	17
6	410,054	3,959	2,598	24
Total	2,925,577	23,608	13,293	120

Note: The data is from the six factories included in the study. The data spans from March 2013 to July 2016. A “Mover” is defined as a worker who is observed at more than one production line during the sample period.

Table 2: Estimates of Sorting Pattern

	Baseline Model		Including Tenure	Including Date FE	Split Sample	Bias Correction	Covariance Shrinkage
	Estimate (1a)	Bootstrap SE (1b)					
$Var(y)$	0.273		0.273	0.273	0.273	0.273	0.273
$Var(\theta)$	0.015	(0.001)	0.015	0.015	0.017	0.014	0.014
$Var(\psi)$	0.018	(0.001)	0.019	0.018	0.019	0.020	0.018
$Var(\psi)/Var(\psi + \theta)$	0.663	(0.032)	0.716	0.700	0.684	0.566	0.519
$Corr(\psi, \theta)$	-0.160	(0.018)	-0.166	-0.180	-0.161	-0.223	-0.107

Note: Table 2 reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). The regressions are estimated by OLS.  $\theta$  corresponds to the worker fixed effect;  $\psi$  to the manager fixed effect. The data includes daily worker-level data from six garment factories. The data spans over three years, from March 2013 to July 2016. Our sample consists of 23,608 workers and 120 production lines (and corresponding line managers). The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls in our baseline specification in column 1a includes: style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style. Column 1b reports bootstrap standard errors for the estimates in column 1a. To construct our bootstrap standard errors, we construct residuals and randomly resample the residuals stratifying by manager-worker pair to preserve the match structure of the observations. We then re-estimate the line and worker fixed effects. We repeat this procedure 100 times. In column 2 we additionally control for both worker tenure in the data and worker tenure on the line, measured respectively as the number of work-days since the worker is observed in the data the first time, and the number of work-days since she started work on the line she is currently observed at at time  $t$ . In column 3 we add a fixed effect for every day in the data. In column 4 we perform a split-sample approach based on Finkelstein et al. (2016) and Best et al. (2019) to account for estimation error. More specifically, we randomly split our sample in half, stratifying by manager-worker pair. We then estimate equation (1) by OLS separately on each sample. We compute each statistic for each sample and then take the average across the two samples. In column 5 we implement the Andrews et al. (2008) bias correction procedure to deal with limited mobility bias. In column 6 we implement the covariance shrinkage method suggested by Best et al. (2019). We use our bootstrap estimation to construct the variance of our manager and worker fixed effects. To account for the covariance of the estimation errors of the manager and workers fixed effects, we follow the shrinkage approach proposed by Best et al. (2019): let  $\hat{\Theta}$  be a vector with the estimated worker and manager fixed effects. Then, the shrinkage matrix  $\Lambda^*$  is defined as  $\arg \min_{\Lambda} \mathbf{E} \left[ \left( \Theta - \Lambda \hat{\Theta} \right) \left( \Theta - \Lambda \hat{\Theta} \right)' \right]$ . That is, we find the weights  $\Lambda$  that minimize the expected mean squared error of the prediction of the linear combination of worker and manager fixed effects. We then “shrink” the estimated worker and manager fixed effects by multiplying them by such weights.

Table 3: Estimates of Sorting Pattern: Productivity vs Wages

	Productivity (1)	Wages (2)
$Var(y)$	0.2729	0.0168
$Var(\theta)$	0.0150	0.0105
$Var(\psi)$	0.0176	0.0001
$Var(\psi)/Var(\psi + \theta)$	0.6629	0.0140
$Corr(\psi, \theta)$	-0.1604	-0.0221

Note: Table 3 reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity (column 1) and wages (column 2) as outcomes ( $y$ ). The regressions are estimated by OLS.  $\theta$  corresponds to the worker fixed effect;  $\psi$  to the manager fixed effect. The data includes daily worker-level data from six garment factories. The data spans over three years, from March 2013 to July 2016. Our sample consists of 23,608 workers and 120 production lines (and corresponding line managers). The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Table 4: Daily Probability of Moves Between Worker and Manager Types

		Worker Type	
		High	Low
Manager Type	High	0.19%	0.88%
	Low	0.75%	0.56%

Note: The table reports the daily probability of observing the following events: (i) a High type worker moving to a High type manager; (ii) a High type worker moving to a Low type manager; (iii) a Low type worker moving to a High type manager; (iv) a Low type worker moving to a Low type manager. Workers and managers are assigned to the High and Low types based on quartiles of the fixed effects from the estimation of equation (1). See Table 2 for details of the estimation. Workers and managers in the top quartile of the fixed effects are assigned to the High type; workers and managers in the bottom quartile of the fixed effects are assigned to the Low type.



Table 5: Heterogeneity by Worker Characteristics

	$Corr(\theta, \psi)$	
	High	Low
Grade	-0.240	-0.175
Salary	-0.169	-0.168
<i>Sample: All Workers</i>		
Outside Homeline	-0.165	
Homeline	-0.126	
<i>Sample: Movers</i>		
Outside Homeline	-0.169	
Homeline	-0.169	

Note: The table reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). The regressions are estimated by OLS.  $\theta$  corresponds to the worker fixed effect;  $\psi$  to the manager fixed effect. The data includes daily worker-level data from six garment factories. The data spans from March 2013 to July 2016. Our sample consists of 120 production lines and 23,608 workers. High grade workers are those in the top skill level, called “A+++”, and correspond to roughly 30% of the sample. Workers are split into high and low salary groups based on median salary. The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Table 6: Supply Chain Constraints Reported by Production Managers

Panel A: Concerns Related to Meeting Targets	Mean
<i>Monetary loss to firm from falling behind with order</i>	51%
<i>Firm risks losing customer from falling behind</i>	33%
<i>Own line has fallen behind with order</i>	19%
Panel B: Steps Taken to Meet Targets	Mean
<i>Would move workers to avoid falling behind</i>	91%
<i>Would move good performers to slow lines</i>	97%
<i>Would move poor performers to slow lines</i>	3%

Note: Data is from the survey of 80 production managers conducted in the six factories in the study.

Table 7: Heterogeneity by Buyer Characteristics

	Large Buyers (1)	Small Buyers (2)
$Corr(\psi, \theta)$	-0.173	-0.117

Note: The table reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). The regressions are estimated by OLS. The data includes daily worker-level data from six garment factories. The data spans from March 2013 to July 2016. Our sample consists of 120 production lines and 23,608 workers. Buyers are classified as either “Large” or “Small” using information on the total number of orders they placed with this firm over the sample period covered by our buyer data, which goes from 2012 to 2015. We define as Large Buyers those in the top decile of total number of orders placed, and as Small Buyers all other buyers. The correlations between manager and worker fixed effects are computed separately for those production lines producing for Large and for Small buyers. The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Figure 1A: Dispersion in Worker Productivity

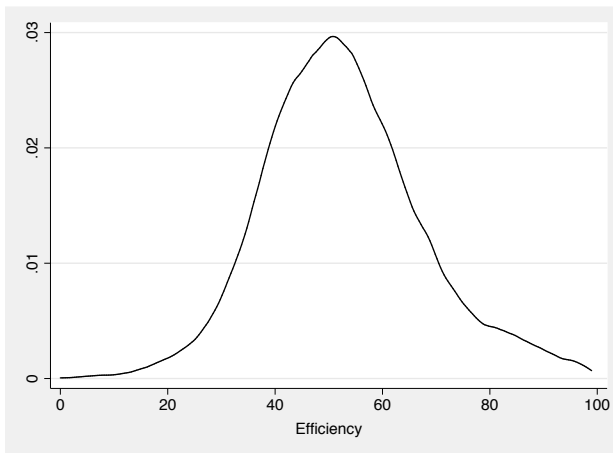
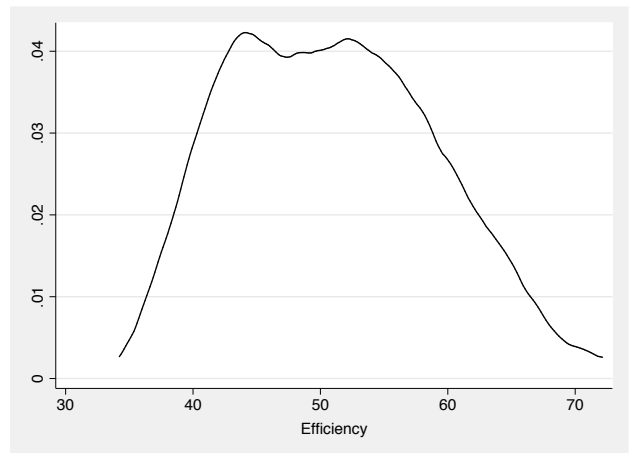


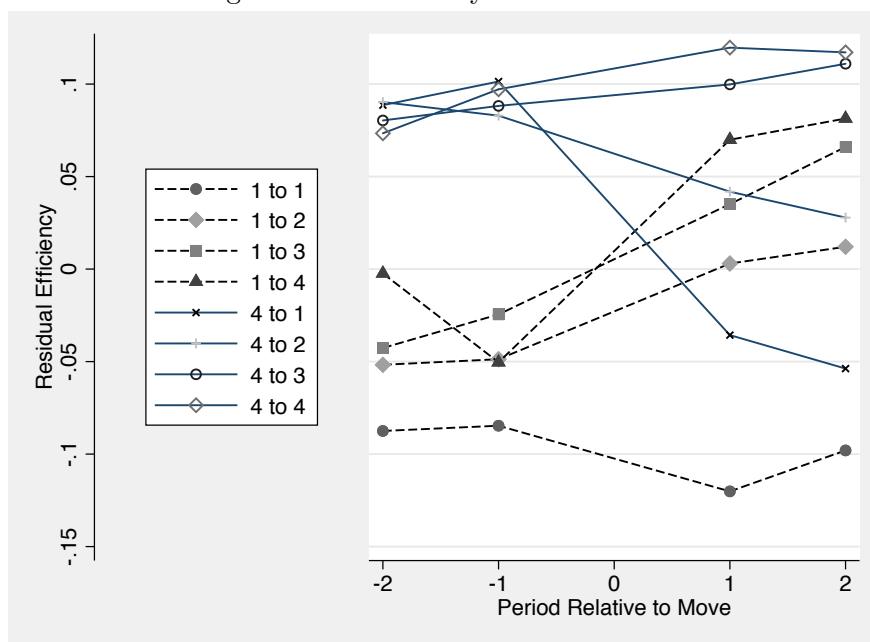
Figure 1B: Dispersion in Manager Productivity



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Note: Figure 1A and 1B show the distribution of the average efficiency of workers and managers, across the six factories included in our study. Efficiency is pooled across days, so that in each graph there is a single observation for each worker and for each manager. The data spans from March 2013 to July 2016. The sample is defined in Table 1. Our measure of productivity is daily efficiency, which equals the percentage of the target quantity of a particular garment that is achieved per day. The target quantity is calculated using a measure of garment complexity called the standard allowable minute (SAM), which is equal to the number of minutes that a particular garment should take to produce.

Figure 2: Event Study Around Moves



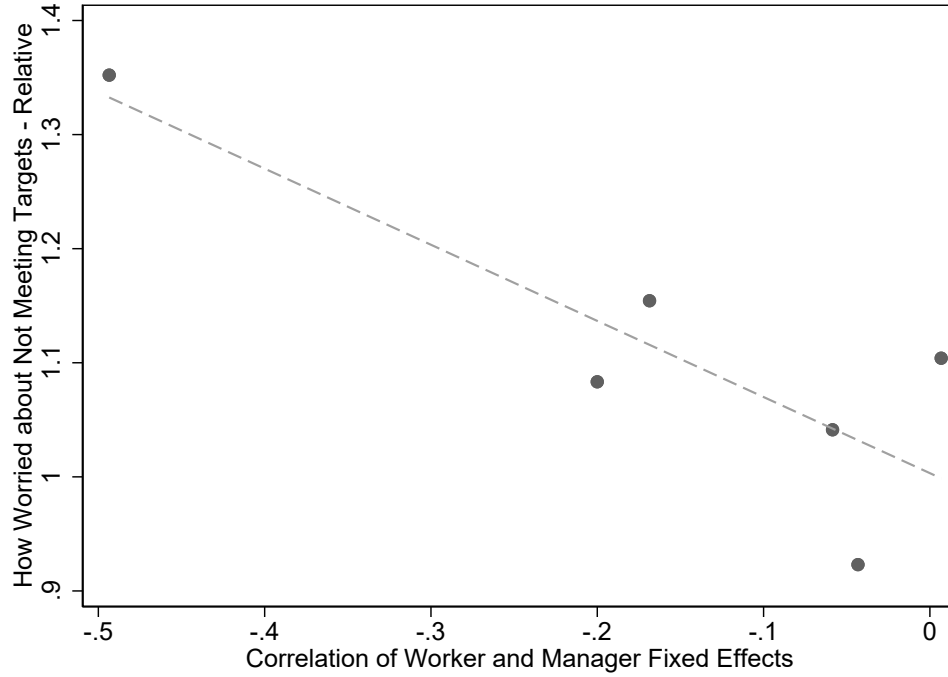
Note: We rank movers in terms of: (i) quartiles of average log-efficiency of the production line they moved away from; and (ii) quartiles of the average log-efficiency of the production line they moved to, where average log-efficiency is computed over the entire sample period and quartiles are computed by factory. The Figure then plots the average residual log-efficiency of the mover on the  $y$ -axis, computed 6 to 10 days ( $Period = -2$ ) and 1 to 5 days ( $Period = -1$ ) before the move from the origin line, and 1 to 5 days ( $Period = 1$ ) and 6 to 10 days ( $Period = 2$ ) after the move to the new destination line, on the  $x$ -axis. The graph only considers moves away from either lines in the top quartile (i.e. lines in quartile 4) or lines in the bottom quartile (i.e. lines in quartile 1). The sample for the graph is restricted to the balanced sample of workers continuously employed at the origin line for at least 10 days prior to the move, and continuously employed at the destination line for at least 10 days after the move. To calculate worker-level residual log-efficiency we run a regression of log daily efficiency of the worker on: factory fixed effects; year, month and day of the week fixed effects; style fixed effects; tenure (days) of the worker in the data; tenure (days) of the worker at the line; finally, we include the experience of the line/manager in producing the current style in the current production run, as measured by the number of consecutive days spent producing that style. We use this regression to calculate residual efficiency of each worker.

Figure 3: Concerns of Production Managers



Note: Data is from the survey of 80 production managers conducted in the six factories in the study. We asked managers to indicate the importance of four potential concerns in their operations: (i) lines not meeting their target/running slow; (ii) worker absenteeism; (ii) line manager absenteeism and (iv) customers not paying for their order on time. Managers were asked to use a 1 to 5 scale to indicate the importance of each concern, with 1 meaning “not worried at all”, and 5 meaning “very worried”. The Figure reports the average for each question.

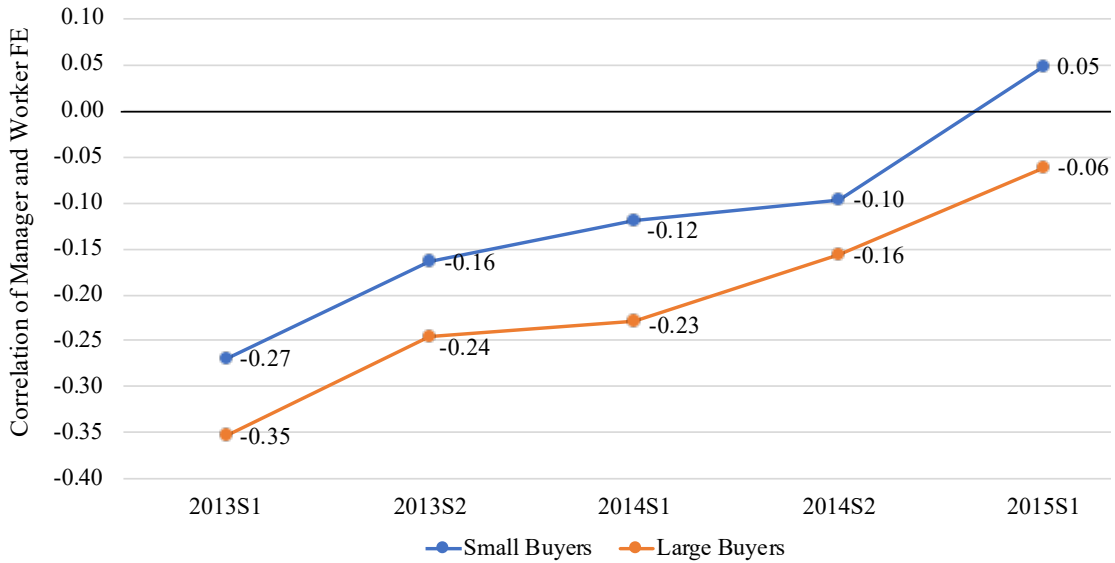
Figure 4: Heterogeneity in Assortative Matching by Manager Concerns



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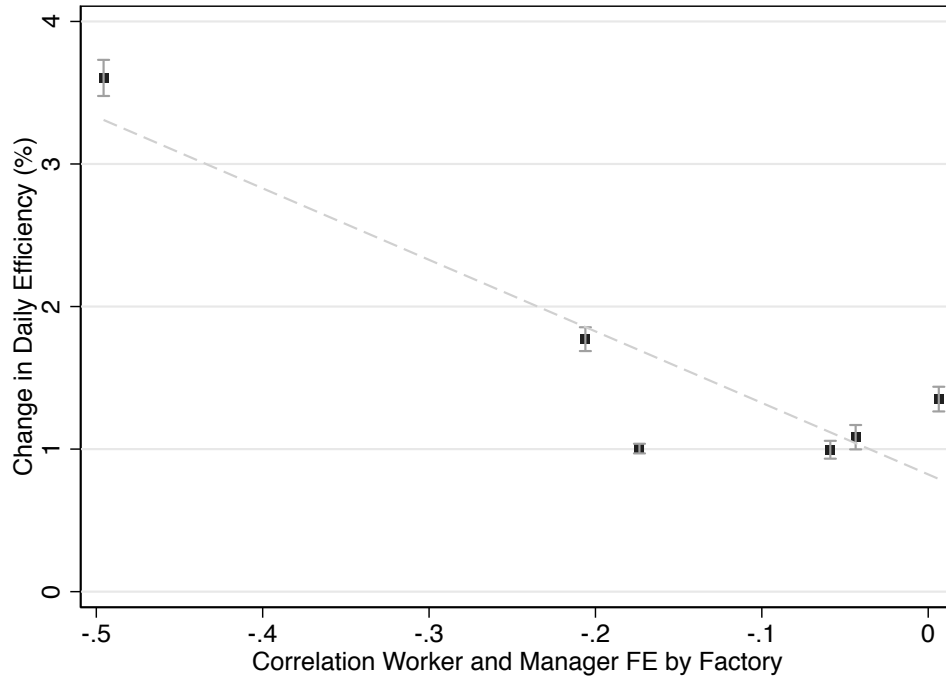
Note: The figure plots on the  $x$ -axis the estimated correlations between the worker and manager fixed effects from the estimation of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome; and on the  $y$ -axis the factory-level relative average importance of concerns related to falling behind with orders and not meeting targets, from the survey of 80 production managers conducted in the six factories in the study. Specifically, for each factory, we divide the average reported concern about lines not meeting deadlines by the within-factory average of all concerns managers were asked about. We then plot this measure on the  $y$ -axis. The Figure also shows the line of best fit from an OLS regression of the relative average importance of concerns related to falling behind with orders and not meeting targets, on the degree of NAM in the factory. For more details on the estimation of equation (1) see Table 2.

Figure 5: Evolution of Assortative Matching over Time, by Buyer Characteristics



Note: The figure reports estimates of the correlation between manager and worker fixed effects, computed by semester and type of buyer. Buyers are classified as either “Large” or “Small” using information on the total number of orders they placed with this supplier over the sample period covered by our buyer data, which goes from 2012 to 2015. We define as Large Buyers those in the top decile of total number of orders placed, and as Small Buyers all other buyers. The correlations between manager and worker fixed effects are computed separately for those production lines producing for Large and for Small buyers, and separately by semester. We estimate equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). The regressions are estimated by OLS. The data includes daily worker-level data from six garment factories. The estimation is conducted on the full sample, but we report the correlations between the manager and worker fixed effects only over those time periods for which we have a balanced sample of factories and lines, in order to avoid the possibility that changes over time are driven by sample selection. Our sample consists of 120 production lines and 23,608 workers. The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Figure 6: Simulated Productivity Gains from Labor Reallocation - Perfect Positive Sorting



Note: The figure plots the simulated productivity gains from implementing the perfect positive sorting allocation, across the six factories in our data, against the estimated correlations between the worker and manager fixed effects from the estimation of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome. The simulation is conducted as follows: a day is randomly extracted from the sample; on that day, the allocation of workers to managers is observed, together with the fixed effects of the workers and the managers; the perfect positive assortative matching allocation is then implemented by assigning the workers with the highest fixed effects to the manager with the highest fixed effects and so on, respecting the line sizes observed in the data. Worker productivity is then predicted using the estimated equation (1), but with workers and managers matched following perfect positive assortative matching. Log efficiency is then exponentiated to recover the counterfactual productivity in levels. This is then summed across all workers and all managers. This procedure is repeated on 1,000 randomly extracted days. We report the mean increase in daily efficiency across the simulation, together with the 95% confidence intervals, where bootstrap standard errors are used to construct the confidence intervals. The Figure also shows the line of best fit from an OLS regression of the average efficiency gain from reallocation, on the degree of NAM in the factory. For more details on the estimation of equation (1) see Table 2.



## Appendix Tables and Figures

Table A1: Distribution of Number of Managers/Lines Workers are Observed at

N. Lines seen at	Freq.	Percent
1	10,315	43.69
2	5,781	24.49
3	3,434	14.55
4	1,826	7.73
5	1,088	4.61
6	654	2.77
7	299	1.27
8	112	0.47
9	57	0.24
10	26	0.11
11	7	0.03
12	5	0.02
13	4	0.02
Total	23,608	100

Note: The Table reports the distribution of number of managers/lines that workers in the sample are observed at, during the sample period. The data is from the six factories included in the study. The data spans from March 2013 to July 2016.

Table A2: Contribution of Worker, Manager and Match Effects to Explaining Productivity

	(1)	(2)	(3)	(4)	(5)
N	2,925,577	2,925,577	2,925,577	2,925,577	2,925,577
$R^2$	0.2703	0.2949	0.3281	0.3324	0.3557
$R^2$ Adjusted	0.2699	0.2945	0.3223	0.3266	0.3433
Time FE	Yes	Yes	Yes	Yes	Yes
Manager FE	No	Yes	No	Yes	No
Worker FE	No	No	Yes	Yes	No
Worker-by-Manager FE	No	No	No	No	Yes

Note: Table A2 reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). The regressions are estimated by OLS. The data includes daily worker-level data from six garment factories. The data spans from March 2013 to July 2016. Our sample consists of 23,608 workers and 120 production lines (and corresponding line managers). The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that line/manager  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Table A3: Do Changes in Productivity Predict the Direction of Moves?

Panel A	D[1 to 1]	D[1 to 2]	D[1 to 3]	D[1 to 4]
$\Delta$ Efficiency	0.0218 (0.0246)	-0.0112 (0.0249)	-0.00589 (0.00905)	-0.00472 (0.00786)
Observations	9,156	9,156	9,156	9,156
Panel B	D[2 to 1]	D[2 to 2]	D[2 to 3]	D[2 to 4]
$\Delta$ Efficiency	0.0262 (0.0386)	-0.0215 (0.0468)	0.00482 (0.0175)	-0.00959 (0.0324)
Observations	6,683	6,683	6,683	6,683
Panel C	D[3 to 1]	D[3 to 2]	D[3 to 3]	D[3 to 4]
$\Delta$ Efficiency	0.00617 (0.0251)	0.00145 (0.0414)	0.00316 (0.0335)	-0.0108 (0.0168)
Observations	6,616	6,616	6,616	6,616
Panel D	D[4 to 1]	D[4 to 2]	D[4 to 3]	D[4 to 4]
$\Delta$ Efficiency	-0.0151 (0.0119)	0.0215 (0.0330)	0.0108 (0.00941)	-0.0173 (0.0368)
Observations	5,919	5,919	5,919	5,919

Note: In Table A3 we rank movers in terms of: (i) quartiles of average log-efficiency of the production line they moved away from; and (ii) quartiles of the average log-efficiency of the production line they moved to, where average log-efficiency is computed over the entire sample period and quartiles are computed by factory. The Table reports the results of OLS regressions where the dependent variables are the conditional probabilities of moving from a line in the  $X$  quartile to a line in the  $Y$  quartile. Panel A only considers moves away from lines in quartile 1; Panel B only considers moves away from lines in quartile 2; Panel C only considers moves away from lines in quartile 3; and Panel D only considers moves away from lines in quartile 4. For example, the variable D[1 to 1] takes value one if the worker moves from a line in quartile 1 to another line in quartile 1, and zero otherwise. We regress such dummy variables on the change in average worker-level log efficiency between the second week and the first week before the move. The sample is restricted to the workers continuously employed at the origin line for at least two weeks prior to the move. All regressions further control for the following covariates: factory fixed effects; style of the origin and destination manager/line fixed effects; tenure (days) in the data; tenure in the data squared and cubic; tenure (days) on the current line; tenure on the current line squared and cubic; number of days the line has been working on a specific style; days on a specific style squared and cubic. The Table reports OLS regression coefficients, with standard errors clustered at the manager/line level in parentheses.

Table A4: Determinants of the Number of Workers Assigned to each Manager/Line

	Number of Workers (1)	Number of Workers (2)	Number of Workers (3)
Standardized Manager FE	-0.0414 (0.708)		
Above Median Manager FE (Yes = 1)		-1.546 (1.318)	
Days Since Start of Order			0.0291 (0.0427)
Observations	49,976	49,976	49,976
Mean of Dep Var	58.54	58.54	58.54

Note: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . OLS regression coefficients, with standard errors clustered at the manager/line level in parentheses. The dependent variable is the number of workers assigned to the manager/line on day  $t$ . We control for style fixed effects to account for variation in productivity due to complexity of the style and size of the order, as well as factory, year, month and day of the week fixed effects, to account for common seasonality and growth in productivity across lines. In column 1 the independent variable is the standardized estimated manager fixed effect from the estimation of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcomes ( $y$ ). In column 2 we include a dummy variable that is equal to one if the estimated manager fixed effect is above the median and 0 otherwise. In column 3 we include the number of days the line has been working on a specific style. For more details on the estimation of equation (1) see Table 2.

Table A5: Production Function Estimates

	<i>3 Months</i>	<i>3 Months</i>	<i>4 Months</i>	<i>4 Months</i>
	ln(efficiency)	ln(efficiency)	ln(efficiency)	ln(efficiency)
	(1)	(2)	(3)	(4)
Manager Type	0.0173*** (0.00582)	0.0182*** (0.00667)	0.0134** (0.00544)	0.0161*** (0.00613)
Worker Type	0.0102*** (0.00382)	0.00942** (0.00426)	0.0116*** (0.00366)	0.0124*** (0.00410)
Manager Type $\times$ Worker Type	-0.000890 (0.000695)	-0.000699 (0.000692)	-0.000596 (0.000598)	-0.000877 (0.000679)
Observations	1,396,661	919,677	1,123,444	916,741
Mean of Dep Var	3.853	3.853	3.858	3.858
Sample of Workers	All	Movers	All	Movers

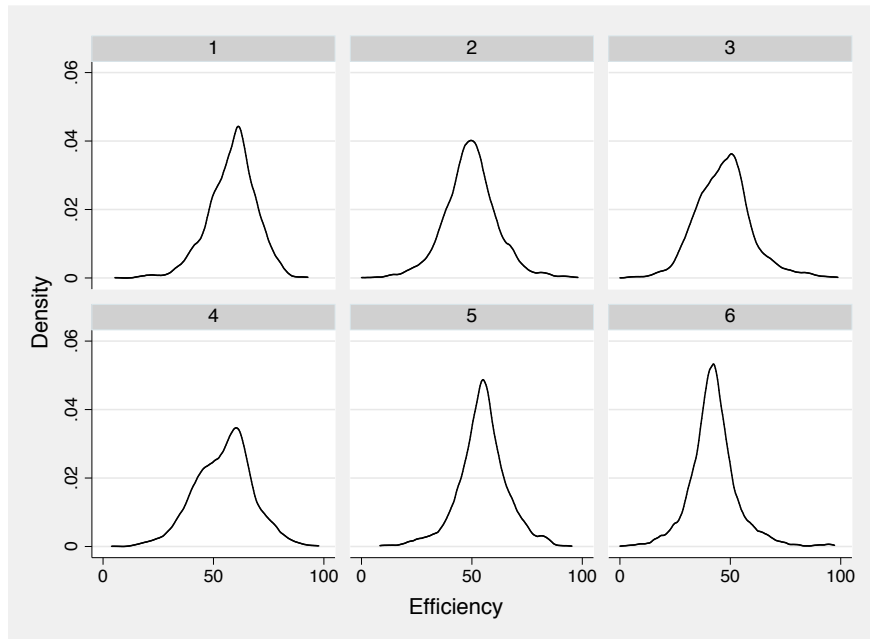
Note: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . OLS regression coefficients, with standard errors clustered at the manager/line level in parentheses. The dependent variable is worker log daily efficiency. We control for style fixed effects to account for variation in productivity due to complexity of the style and size of the order, as well as year, month and day of the week fixed effects, to account for common seasonality and growth in productivity across lines. The Worker Type and Manager Type variables are constructed by taking averages of raw worker-level and manager/line-level efficiency in the first three months (columns 1-2) or four months (columns 3-4) of data. The Worker Type and Manager Type variables then report quartiles of such average efficiency of workers and managers, respectively. The estimation of the production function is then performed on the later time periods, and so excluding the first three months of data (columns 1-2) or the first four months of data (columns 3-4).

Table A6: Production Function Estimates: Controlling for Co-Worker Productivity

	<i>3 Months</i>	<i>3 Months</i>	<i>4 Months</i>	<i>4 Months</i>
	ln(efficiency)	ln(efficiency)	ln(efficiency)	ln(efficiency)
	(1)	(2)	(3)	(4)
Manager Type	0.0197** (0.00803)	0.0194* (0.0104)	0.0217*** (0.00788)	0.0206** (0.00985)
Worker Type	0.0103*** (0.00382)	0.0108** (0.00464)	0.0121*** (0.00362)	0.0139*** (0.00454)
Manager Type $\times$ Worker Type	-0.000918 (0.000690)	-0.000887 (0.000712)	-0.000700 (0.000588)	-0.00111 (0.000697)
Share of High Type Workers	-0.0137 (0.0382)	-0.0108 (0.0473)	-0.0483 (0.0410)	-0.0216 (0.0486)
Observations	1,396,661	919,677	1,123,444	916,741
Mean of Dep Var	3.853	3.853	3.858	3.858
Sample	All	Movers	All	Movers

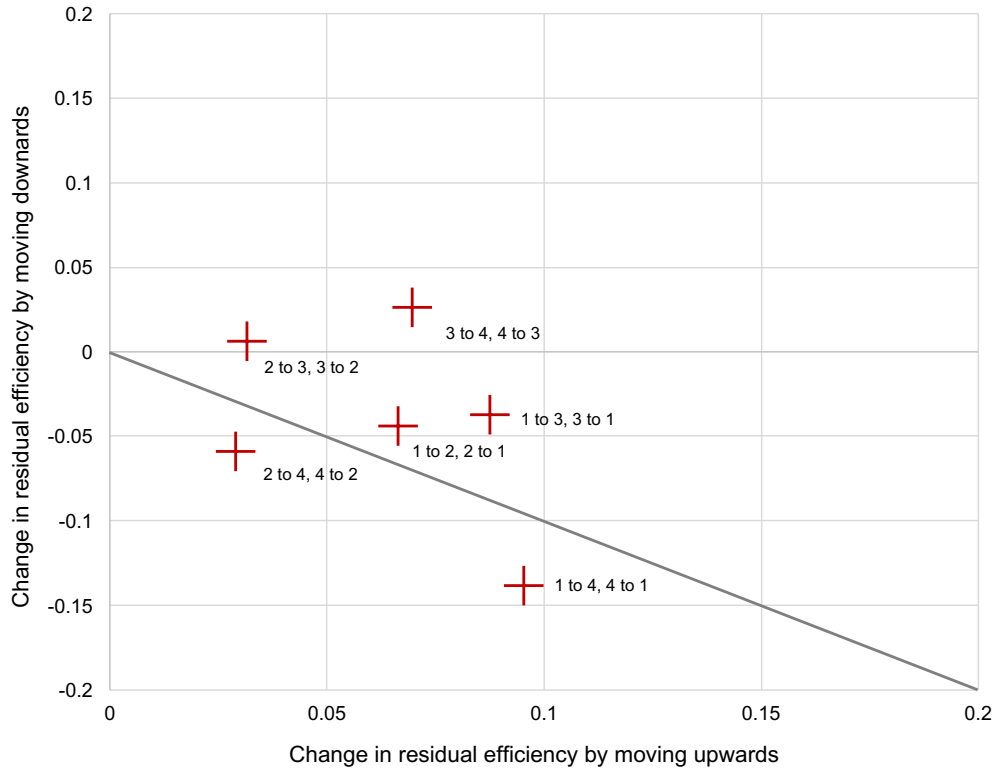
Note: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . OLS regression coefficients, with standard errors clustered at the manager/line level in parentheses. The dependent variable is worker log daily efficiency. We include style fixed effects to account for variation in productivity due to complexity of the style and size of the order, as well as year, month and day of the week fixed effects, to account for common seasonality and growth in productivity across lines. The Worker Type and Manager Type variables are constructed by computing averages of raw worker-level and manager/line-level efficiency in the first three months (columns 1-2) or four months (columns 3-4) of data. The Worker Type and Manager Type variables then report quartiles of such average efficiency of workers and managers, respectively. The estimation of the production function is then performed on the later time periods, and so excluding the first three months of data (columns 1-2) or the first six months of data (columns 3-4). The variable Share of High Type Workers measures the share of workers in the top quartile assigned to manager  $j$  at the same time as worker  $i$ .

Figure A1: Dispersion in Worker Productivity, by Factory



Note: Figure A1 shows the distribution of the average efficiency of the workers by factory. The data includes daily worker-level data from the six garment factories. Efficiency is pooled across days, so that in each graph there is a single observation for each worker. The data spans from March 2013 to July 2016. The sample is defined in Table 1. Our measure of productivity is daily efficiency, which equals the percentage of the target quantity of a particular garment that is achieved per day. The target quantity is calculated using a measure of garment complexity called the standard allowable minute (SAM), which is equal to the number of minutes that a particular garment should take to produce.

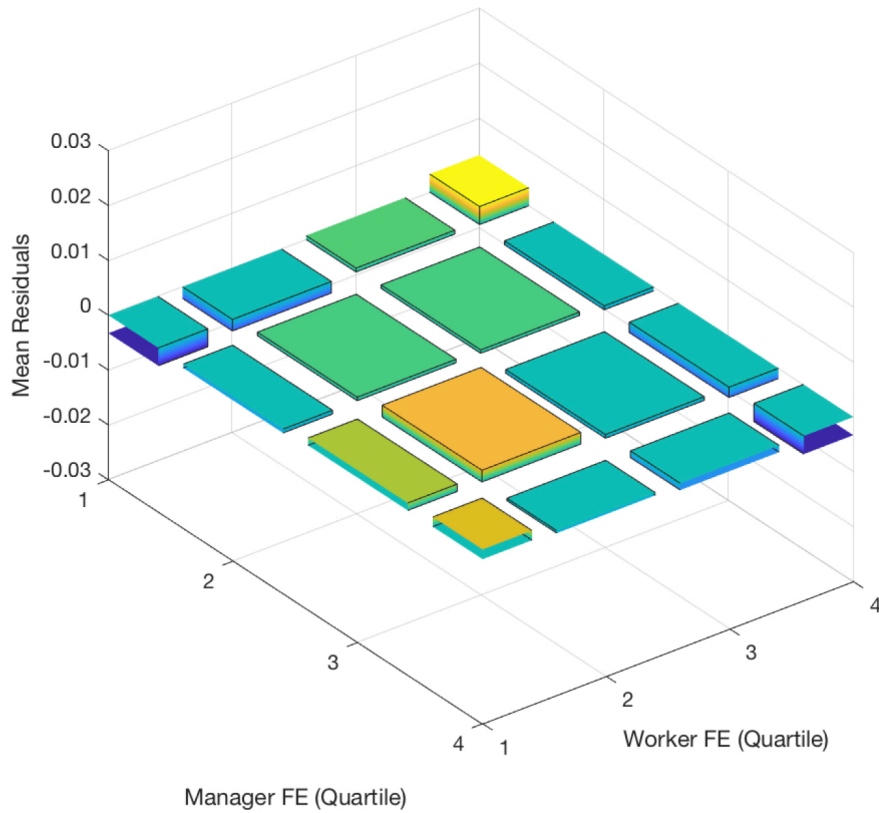
Figure A2: Symmetry Test for Endogenous Mobility



Note: We rank movers in terms of: (i) quartiles of average log-efficiency of the production line they moved away from; and (ii) quartiles of the average log-efficiency of the production line they moved to, where average log-efficiency is computed over the entire sample period and quartiles are computed by factory. The Figure then plots the average change in residual log-efficiency for movers from lines in quartile  $X$  to quartile  $Y$ , against the change in residual log-efficiency for movers in the opposite direction. So for example, the point labelled “2 to 4, 4 to 2” corresponds to the average change for movers from lines in quartile 2 to quartile 4, plotted against the change for movers from lines in quartile 4 to quartile 2. The changes are calculated for average residual log-efficiency in the two weeks before the move and the two weeks after the move. The solid line corresponds to the 45 degree line. The sample for the graph is restricted to the balanced sample of workers continuously employed at the origin line for at least 10 days prior to the move, and continuously employed at the destination line for at least 10 days after the move. To calculate worker-level residual log-efficiency we run an OLS regression of log daily efficiency of the worker on: factory fixed effect; year, month and day of the week fixed effects; tenure (days) in the data; tenure (days) at the line; number of days the line has been working on a particular style. We use this regression to calculate residual efficiency of each worker. Standard errors are clustered by manager/line in this regression.

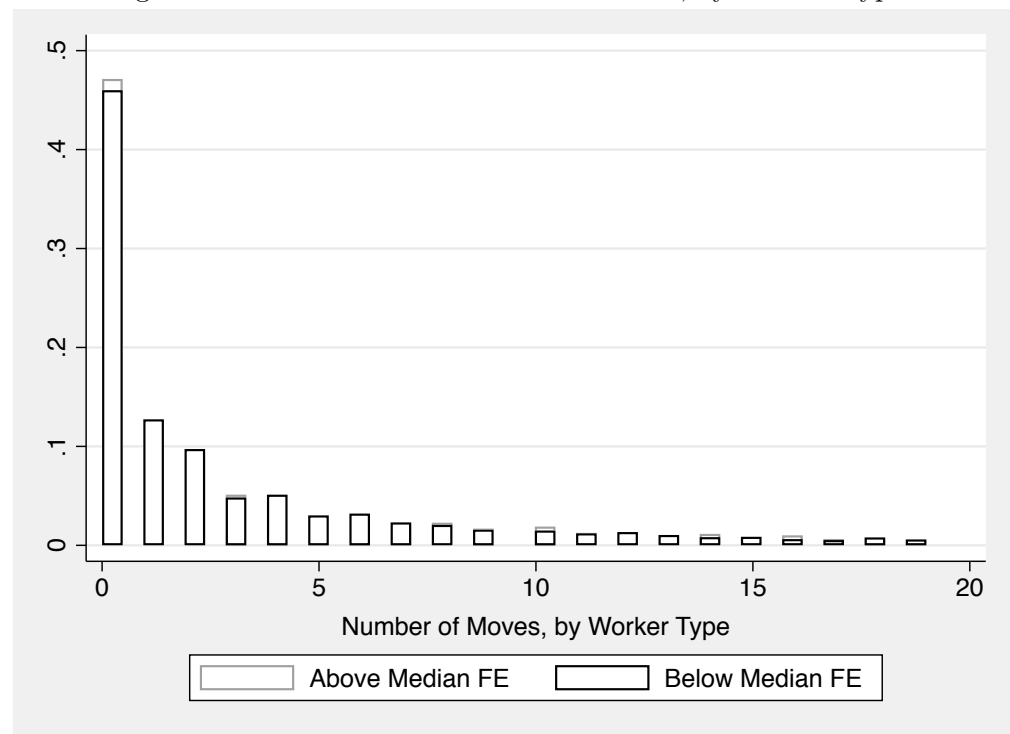


Figure A3: Mean Residuals by Quartile of Worker and Manager Fixed Effects



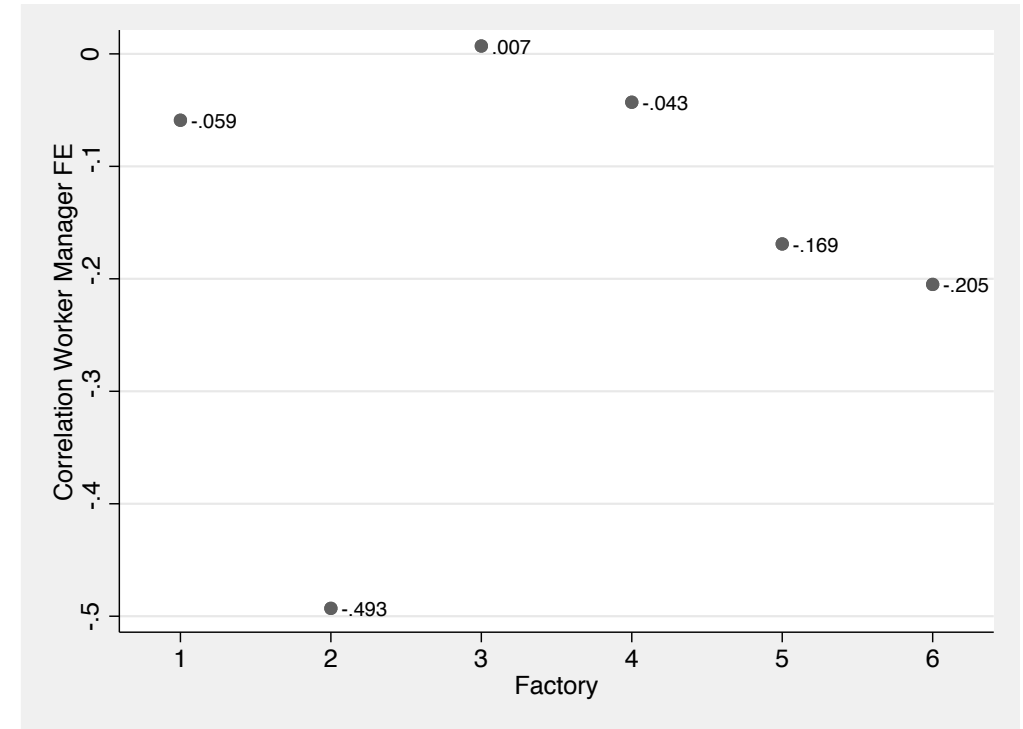
Note: This figure reports estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). Specifically, the figure reports mean residuals by quartile of the estimated worker and manager fixed effects. The regressions are estimated by OLS. The data includes daily worker-level data from six garment factories. The data spans from March 2013 to July 2016. Our sample consists of 23,608 workers and 120 production lines (and corresponding line managers). The statistics reported in the table are first computed by estimating the econometric model separately for each factory, and then a weighted average across factories is calculated, weighted by the sample share of each factory. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that line/manager  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Figure A4: Distribution of Number of Moves, by Worker Type



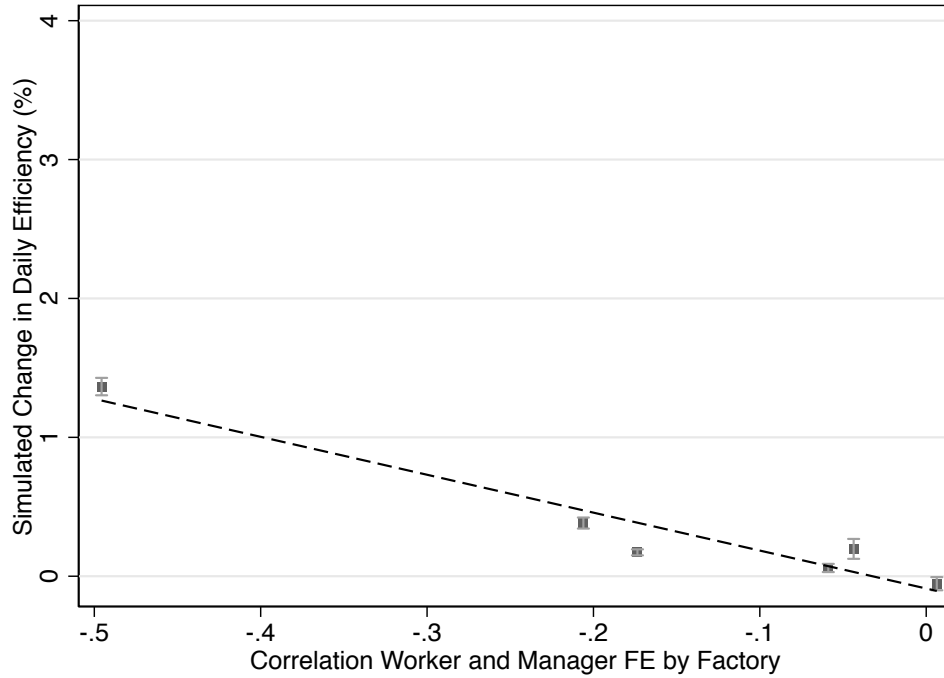
Note: Figure A4 shows the distribution of the number of moves for workers above and below the median estimated fixed effect from the estimation of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome ( $y$ ). The data includes daily worker-level data from the 6 garment factories. The data spans from March 2013 to July 2016. Our sample consists of 120 production lines and 23,608 workers. A “move” is defined as a reallocation away from the current production line and to a different one. For more details on the estimation of equation (1) see Table 2.

Figure A5: Sorting Estimates: Correlation of Worker and Manager FE by Factory



Note: Figure A5 reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcomes ( $y$ ). The estimates are reported by factory. The regressions are estimated by OLS. The data includes daily worker-level data from six garment factories. The data spans from March 2013 to July 2016. Our sample consists of 120 production lines and 23,608 workers. The set of time-varying controls includes style (or garment) fixed effects; year, month and day of the week fixed effects; and the experience that manager/line  $J(i, t)$  has in producing the current style at date  $t$  in the current production run, as measured by the number of consecutive days spent producing that style.

Figure A6: Simulated Productivity Gains from Labor Reallocation - Random Matching



Note: The Figure plots the simulated productivity gains from implementing the random matching allocation, across the six factories in our data, against the estimated correlations between the worker and manager fixed effects from the estimation of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using productivity as outcome. The simulation is conducted as follows: a day is randomly extracted from the sample; on that day, the allocation of workers to managers is observed, together with the fixed effects of the workers and the managers; the random matching allocation is then implemented by randomly assigning workers to managers/lines, respecting the line sizes observed in the data. Worker productivity is then predicted using the estimated equation (1), but with workers and managers matched following random matching. Log efficiency is then exponentiated to recover the counterfactual productivity in levels. This is then summed across all workers and all lines. This procedure is repeated on 1,000 randomly extracted days. We report the mean increase in daily efficiency across the simulation, together with the 95% confidence intervals, where bootstrap standard errors are used to construct the confidence intervals. The Figure also shows the line of best fit from an OLS regression of the average efficiency gain from reallocation, on the degree of NAM in the factory. For more details on the estimation of equation (1) see Table 2.