Absenteeism, Productivity, and Relational Contracts Inside the Firm*

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Abstract

We study relational contracts among managers using unique data that tracks transfers of workers across teams in Indian ready-made garment factories. We focus on how relational contracts help managers cope with worker absenteeism shocks, which are frequent, often large, weakly correlated across teams, and which substantially reduce team productivity. Together these facts imply gains from sharing workers. We show that managers respond to shocks by lending and borrowing workers in a manner consistent with relational contracting, but many potentially beneficial transfers are unrealized. This is because managers' primary relationships are with a very small subset of potential partners. A borrowing event study around main trading partners' separations from the firm reinforces the importance of relationships. We show robustness to excluding worker moves least likely to reflect relational borrowing responses to idiosyncratic absenteeism shocks. Counterfactual simulations reveal large gains to reducing costs associated with forming and maintaining additional relationships among managers.

Keywords: implicit contracts, productivity, misallocation, absenteeism, management, supervisors, ready-made garments, India

JEL Codes: D23, D86, L14, L23, M54

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1 Introduction

Relational contracts – informal agreements that leverage repeated interactions to overcome information or contractual specification and enforcement problems – are essential building blocks of the theory of the firm (Baker et al., 1994, 2001; Chassang, 2010; Gibbons and Roberts, 2012; Levin, 2003; MacLeod and Malcomson, 1989). Workplace collaboration among teams and across bosses and subordinates is the result of many non-contractible transactions that are disciplined by the promise of future rents or reciprocation. Yet, despite their fundamental importance, most of what we know about the form and function of relational contracts within the firm is anecdotal (Board, 2011; Gibbons and Henderson, 2012a,b; Helper and Henderson, 2014; Johnson et al., 2002). This is perhaps unsurprising, given that the numerous favors and promises among colleagues that make organizations run smoothly seem too ordinary to meticulously record. In contrast, the availability of detailed data on transactions *between* firms has spawned a rich literature on the causes and consequences of imperfect contract enforcement in firm-to-firm relationships (Atalay et al., 2019; Atkin and Khandelwal, 2019; Banerjee and Duflo, 2000; Cajal-Grossi et al., 2019; Hansman et al., 2017; Khwaja et al., 2008; Lafontaine and Slade, 2007; Macchiavello and Miquel-Florensa, 2017; Macchiavello and Morjaria, 2015, 2017; McMillan and Woodruff, 1999).

As a result of this scarcity of records of cooperation among coworkers within firms, many basic questions remain largely unanswered. For example, how prevalent are relational contracts among coworkers? What specific frictions do they help overcome? How well do they work – that is, how close are outcomes to first-best? What barriers prevent relationships from forming or maturing, and do these barriers lead to sub-optimal quantity and quality of relationships? Our study aims to fill part of this knowledge gap. We shed light on some of these questions using unique data on relationships among managers in a large ready-made garment firm in India. Workers in this firm are organized into production lines, and each line is typically led by one manager. Managers play a key role in determining line productivity in this setting (Adhvaryu et al., 2021, 2023b; Boudreau, 2020; Macchiavello et al., 2020). They assign sewing machine operators to tasks; deal with bottlenecks in throughput along the line; and monitor and motivate workers to meet production targets (Adhvaryu et al., 2022a).

We focus on one key challenge managers face in this setting – high and often unpredictable worker absenteeism. This challenge is common across organizations in many contexts, particularly so in low-income countries (Banerjee and Duflo, 2006; Chaudhury et al., 2006; Duflo et al., 2012; Kremer et al., 2005). In our sample, for example, the average daily worker absenteeism rate is eleven percent, and for any given production line, the rate is at least twenty percent once in every ten days. We show, via fixed effects as well as instrumental variables specifications, that these fluctuations do indeed have substantial impacts on line productivity, implying that absenteeism is of first-order importance both to managers and to the firm.

How do managers smooth production in the face of this uncertainty? We demonstrate that managers rely on relationships through which they "lend" and "borrow" workers based on absenteeism shocks realized at the start of each production day. The lack of an internal labor market in this setting is likely due to information frictions both within and across levels of the managerial hierarchy. Among line managers, the basic information problem is related to the observability of actual "need." In the few hurried minutes before production begins each day, it is infeasible to verify worker shortages on any particular production line; trade in a spot market would likely break down.[1] Similarly, across managers and their higher-ups, truthfully reporting shortages, optimally reallocating workers, and communicating these changes across the factory workforce is likely to come up against time and span of control constraints. Managers in this setting are also able to identify "unobservable" comparative advantages in particular tasks for their own team's workers (Adhvaryu et al., 2022a); these differences among otherwise similar workers are not readily evident to managers of other lines, which compounds the asymmetric information problem just described. These frictions create potential value in relationships among managers. As one manager aptly conveyed to us, "...we share workers with an understanding that we might need to borrow workers in the future." To study this behavior, we exploit unique administrative data on daily worker absenteeism, line productivity, and, importantly, transfers of workers across managers.[2]

We begin by showing that daily fluctuations in absenteeism are not highly correlated across managers, even for managers working on the same factory floor. This, paired with the concavity of the production function with respect to the number of workers, creates potential value to "borrowing" workers with the promise of repaying that debt in the future. In particular, a manager whose production line would fall behind due to high worker absenteeism could borrow from a colleague

[1] That is, a manager cannot perfectly observe in a the scarce time at the start of the day how many (and/or which) *operations* are left vacant on a given day on a fellow manager's line due to absenteeism, how many (and/or which) workers are present on that other line, and all the ways the configuration of available workers to critical operations maybe adjusted. They can't readily assess bottlenecks that may hinder production on that other line and how hard it will be for that line (both in terms of complexity and number of garments) to complete its order either. Importantly, accurate daily worker-level productivity data is not available to the managers as we explain in Subsection 2.5.

[2] This decentralization of personnel management is quite common. For example, Kuhn and Yu (2021) study menswear outlets in China that are characterized by high turnover. In that context, the firm chose to delegate many aspects of worker discipline and staffing to the sales teams themselves rather than relying on higher layers of management. In particular, sales people are directly involved in the recruitment process via referral solicitations. Relying on production line managers to deal with staffing problems due to absenteeism is not *a priori* the only strategy that could be used by the firm we study. For example, Bartel et al. (2014) study how absenteeism of nurses in the US affects patient care. Rather than having nursing unit managers trading nurses across units within a hospital, they rely on overtime and by covering absences with temporary nurses contracted from external staffing agencies. In our context, however, overtime is restricted by strict labor laws (in addition to buyer compliance oversight) and the firm does not have the capacity to hire a large set of floating workers. This is likely related to the fact that firing cost is extremely high in India in the formal sector and especially for large firms (Adhvaryu et al., 2013; Besley and Burgess, 2004). We nevertheless explore the potential gains for the firm from building a stock of floating workers in the last section.

whose line happened to have incurred a less severe shock that day, presumably with the promise of repaying the favor should the relative states be switched in some future period. We also check that absenteeism is balanced across managers of differing quality or average efficiency and provide evidence that line-day absenteeism is plausibly exogenous in this setting.

We find that while managers do indeed exchange workers in this manner, many potentially beneficial transfers are left unrealized. Most managers have active relationships (i.e., are engaging in regular lending or borrowing of workers) with only two or three colleagues, out of on average more than twenty potential relationships with other managers working in their factories. The average manager forgoes 15-19 partnerships. As a result, for relatively large worker absenteeism shocks, which have the potential to generate substantial productivity losses, we show that managers struggle to leverage relationships to make up for the shortfall in workers.[3]

Most of the seminal models of relational contracts involve a transfer of utility between risk neutral agents; while in our setting managers transfer workers who are inputs in a concave production function. To further study the nature of lending and borrowing behavior among managers, we supplement our study with a simple model capturing these features. Our model delivers predictions in line with seminal relational contract models, showing that the particularity of our setting does not change the key insights presented in the literature.

We test the predictions using a dyadic data set of managers within factories. Worker-by-day data on absenteeism, combined with a precise mapping of workers to lines for every production day, enables us to track transfers of workers across all manager dyads. As expected under relational contracts, we find that borrowing is indeed affected by absenteeism realizations, the maturity of relationships, and transaction costs. One important takeaway from this analysis is that both physical distance *and* "identity-based" distance such as gender, education, age and experience differences between the managers matter for the intensity of transfers in relationships.[4]

We then discuss several additional results and demonstrate the robustness of our main results in several ways. First, we show that the predictions regarding trading patterns are reflected on the extensive margin of any trading between patterns in addition to the intensive margin of quantity of workers traded shown in the main results. Then, we document that managers are more selective

[3]The dip in productivity following absenteeism shocks is consistent with Kuhn and Yu (2021) who find that productivity falls when a sales team member separates from their employer due to short staffing post separation. In their context, because separating workers notify the employer of their intention, the short staffing productivity dip is often mitigated as employers can work to find a replacement rapidly.

[4]That is, not only is it the case that physical distance on the factory floor determines the intensity of trade, but what also matters for these contracting outcomes is the similarity of managers in terms of identity characteristics. This is an important fact because while both types of distance relate to transaction costs, physical distance might also reflect inherent features of the organization of production on factory floors that may make trading more likely for purely technical reasons. Demonstrating that a "softer" distance based on managerial characteristics matters in addition to this provides more robust evidence in support of the predictions of relational contracts set out in the paper.

of the partners with whom they trade their higher productivity workers.[5] We also use the factors of managerial quality identified as most important for productivity in Adhvaryu et al. (2023b) to investigate which types of managers appear to trade most actively. We find that managers exhibiting greater Control (i.e., a stronger belief in their own ability to impact performance rather than acquiescing to fate or chance) are more active traders; while managers exhibiting greater Attention are less active traders, consistent with a greater ability to leverage within line worker-task reassignments to mitigate any potential productivity losses (i.e., to "make do" with the available workers on the line) as shown by Adhvaryu et al. (2022a) in a similar setting.

Moreover, Adhvaryu et al. (2021) provide evidence in a nearly identical setting that upper managers sometimes systematically reorganize workers across lines for many days, shifting high-efficiency workers from high-productivity lines to low-productivity lines when the latter begins a new garment order to preemptively ensure that deadlines for important buyers are met. Accordingly, we check that these worker moves across lines are distinct from the short-term sharing of workers in response to idiosyncratic absenteeism shocks we aim to study here, which is balanced across high- and low-efficiency workers and lines and occurs throughout the duration of the order. We then demonstrate that our results are robust to excluding worker moves most likely to reflect this systematic reorganization of workers across lines (i.e., moves initiated within the first week of an order and moves lasting too many days to likely be responses to absenteeism).

In the last section, we perform several counterfactual simulations to assess the extent to which relationships among managers matter for aggregate (plant-level) productivity. In particular, first we assess what would happen if managers did not share workers at all – i.e., in a world in which there were no relational contracts. We find that aggregate productivity in this world would be roughly 0.2 percent lower than the *status quo* (relational contracting) equilibrium. Next, motivated by the fact that there seem to be very few active relationships per manager, we ask what the gains to increasing the number of trades would be.[6] We trace out a concave function that shows that productivity would increase substantially (by as much as 1.3 percent) if workers could be traded centrally without any frictions (first best), which would translate roughly to a 1.45 million US dollars increase in annual profit for the firm. We find that maximizing the number of relationships would achieve approximately 40% of the productivity gained under the first-best scenario, suggesting that the value of additional relationships to the firm in this context is quite substantial. While increasing the number of partnerships between managers may be done at relatively low cost, we also explore how the firm could further increase productivity by reducing absenteeism or hiring floating workers.

[5] Such behavior is predicted by a generalized version of our model in which worker quality varies.

[6] We note that some opportunity or effort cost likely exists such that managers are not leveraging valuable trading partnerships in the status quo equilibrium, and therefore conceptualize this thought experiment as the introduction of social events to create bonds between managers, some cost-reducing technology such as an app or messaging network that allows for managers to trade workers without having to spend time and effort to meet with or monitor each other.

We find that increasing partnerships to a maximum would achieve 23% of the gains from reducing absenteeism by half. This suggests that while the losses from the misallocation of labor *within* the firm may be less important than the losses from market failures such as those that lead to worker absenteeism partially outside the firm's direct control, the former may be addressed at a lower cost. Indeed, it may be cheaper to foster relationships among existing managers than provide sufficient monetary incentives to workers to reduce absenteeism.

Our paper makes three main contributions. First, much of the rich theoretical basis of organizational economics rests on the idea that repeated interactions among coworkers and between managers and employees create value in settings with incomplete contracting (Baker et al., 1994, 2001, 2002; Chassang, 2010; Gibbons and Roberts, 2012; Levin, 2003; MacLeod and Malcomson, 1989). Yet, despite growing empirical evidence on relational contracts *across* firms, which often benefits from detailed transactions data across buyer-supplier relationships (Atkin and Khandelwal, 2019; Banerjee and Duflo, 2000; Cajal-Grossi et al., 2019; Macchiavello and Miquel-Florensa, 2017; Macchiavello and Morjaria, 2015, 2017; McMillan and Woodruff, 1999), the empirical support for theories within firms is less complete. Specifically, informal agreements between employees within a firm, like those studied here, likely abound both across and within levels of the organizational hierarchy. While a recent body of evidence has documented informal agreements across levels of the hierarchical structure such as subjective performance bonuses between employers and employees (see Akerlof et al. (2022), and Gil and Zanarone (2017); Lazear and Oyer (2013) for reviews), little empirical work to our knowledge exists on informal agreements formed between employees within the same level of the organizational hierarchy.[7] We provide direct empirical characterization of this latter type of agreements by studying relational contracts taking place between peer managers supervising parallel production teams. We produce new evidence that the barriers to relationship formation and maturity are non-trivial, and also that encouraging new relationships by reducing these barriers can result in substantial positive gains for both managers and the firm.

Second, we contribute to the literature in personnel economics that has documented how coworkers impact each other's productivities (Amodio and Martinez-Carrasco, 2018; Bandiera et al., 2010, 2013), as well as how the interaction between workers and their supervisors determines firm productivity (Adhvaryu et al., 2023b; Frederiksen et al., 2017; Hoffman and Tadelis, 2018; Lazear

[7]While Sandvik et al. (2020) do not study existing relational contracts, they devise an experiment in which salespersons are paired to share sales information and tips. In essence, they experimentally form relational interactions between workers and find that sales can improve by as much as 15%. Similarly, Kuhn and Yu (2021) look at menswear sales team productivity around the time a worker announces she will separate from the employer. They do not study relational contracts between team members, but recognize that shortly before a worker leaves, future repeated interactions cannot be exploited, which could help explain productivity dips during that time. Akerlof et al. (2022) investigate what happens when a sweater laid off many workers in response to labor unrest. Their results suggest that workers remaining employed with stronger social connections with workers that were laid off, appear to retaliate by shading their productivity in response to an erosion of relational contracts between management and the workers.

et al., 2015). Our study adds to this literature evidence on how managers can impact the productivity of each other's teams by way of cooperative resource sharing. Our results also add to the large body of empirical evidence on the impacts of management on productivity (Bloom et al., 2016; Bloom and Van Reenen, 2007, 2011; Gosnell et al., 2019; McKenzie and Woodruff, 2016), documenting that one way in which managers contribute to the productivity of their teams is to enable smoothing of resource shocks by way of cooperation with fellow managers.[8]

Finally, we contribute to the understanding of the allocation of talent within firms. The assignment of workers to teams and tasks is a key feature of the organization of production within firms, both in theory (Gibbons and Waldman, 2004; Holmstrom and Tirole, 1989; Kremer, 1993; Lazear and Oyer, 2007; Lazear and Shaw, 2007) and in practice (Adhvaryu et al., 2021, 2022a; Amodio and Di Maio, 2017; Amodio and Martinez-Carrasco, 2018; Bandiera et al., 2007, 2009; Bloom et al., 2010; Burgess et al., 2010; Friebel et al., 2017; Hjort, 2014). We add to these studies by demonstrating that the allocation of workers to teams is governed in part by relational contracts among managers, and that the internal misallocation of labor can be quite costly.

2 Context

2.1 Industry context

We study production line managers at Shahi Exports, Pvt. Ltd., the largest readymade garment manufacturer in India and among the top five largest such firms worldwide.[9] As a labor-intensive manufacturing industry that has characterized the initial stages of industrialization in many parts of the world, but one that today utilizes modern production concepts such as specialization, assembly lines, and lean production, garment manufacturing provides an excellent setting to study the impacts of personnel management practices on productivity.

Shahi Exports is a contract manufacturer for international brands. Orders from brands are allocated by the marketing department of each production division (Knits, Men's, and Ladies') to factories based on capacity and regulatory and/or compliance clearance (i.e., whether a particular factory has been approved for production for that brand given its corporate and governmental standards). Within the factory, the order will then be assigned to a production line by first availability.[10] The order will then be produced in its entirety by that production line and prepared for shipment in advance of the contracted delivery date.

The firm is organized in a hierarchy with many levels. At the lowest level, workers are assigned

[8] Middle managers like the production line supervisors we study are often emphasized as enablers or constrainers of worker productivity (Adhvaryu et al., 2023b; Levitt et al., 2013), particularly in low-income countries and labor-intensive manufacturing settings (Bloom and Van Reenen, 2007; Boudreau, 2020; McKenzie and Woodruff, 2016).

[9] India is the fourth largest exporter of garments in the world (WTO, 2018).

[10] That is, whichever line happens to be finishing its current order when an incoming order is processed will be allocated that new order.

to production lines (of roughly 50-60 workers in the sewing department for example) with a permanently assigned line supervisor (and sometimes other senior workers performing assistant supervisory duties).[11] These line supervisors report to a floor production manager in large factories and to a factory production manager in smaller factories. This level is in charge of screening, hiring, training and onboarding line supervisors. Line supervisors are able to ask advice and input from these production managers when necessary regarding the management of producing an order for on time delivery, but are expected to run their lines autonomously otherwise.[12] As a result, we argue these factory and floor production managers are best conceived of "middle managers," who maintain private knowledge about and a necessary rapport with the (roughly 5 to 10) line supervisors in their charge, but do not work closely enough with workers or particular orders to intervene in day-to-day operations. These middle managers report to the General Manager (GM) of the factory who is in charge of all operations including accounting, finance, HR, etc. This factory-level GM reports in turn to a division CEO and COO who oversee roughly 20 factories, and 3 sets of these executives across 3 divisions of the firm report to the board and managing director of the entire firm. In a related experiment in similar factories, Adhvaryu et al. (2022b) study delegation across these levels of the hierarchy, revealing substantial private information across levels which limits the ability for one level to intervene in the daily decisions of levels below.

2.2 Production process

There are three main stages in the production process. First, fabric is cut into subsegments for different parts of the garment, organized according to groups of operations for each segment of the garment (e.g., sleeve, front placket, collar), and grouped into bundles representing some number of garments (e.g., materials for 20 sleeves or 10 collars). These bundles of materials are then fed into the sewing line at several feeding points according to which segment of the line is producing each segment of the garment. The operations to construct each portion of the garment and ultimately attach these portions together to make complete garments makeup the sewing part of the production process. Finally, the sewn garments go through finishing (e.g., washing, trimming, final quality checking) and packing for shipment in the final stage of the process.

In our study, we focus on the sewing process as this step makes up the majority of the production timeline, utilizes the majority of the labor involved in production, and lends itself to detailed observation of team composition and output as needed for our analysis. In this paper, we leverage production data from 4 factories consisting of a total of 73 sewing production lines. We focus

[11] Managers sometimes ask senior workers on the line to help in doing supervisory tasks such as feeding parts of garments to specific operations while monitoring the production of these critical operations, instead of actually sewing garments themselves. From our discussions with managers, these senior workers play no role in trading.

[12] Indeed, Adhvaryu et al. (2023b) show in a similar context that lines are more productive when managers embrace this autonomy.

the analysis on the spans of consecutive months where the production of most lines is recorded consistently for each factory. As a result, our sample consists of 6-7 consecutive months per factory.[13]

A typical sewing line has 50-60 permanently assigned workers. Each line works on one order at a time, for roughly 3-4 weeks on average, until the order is complete. The sewing process is split into individual machine operations, with each operation typically being completed by one worker assigned to a single machine. In practice, production may deviate from this structure if, for example, several machines and workers are charged with a particular operation which has proven to be slower than expected, or if an extra worker is staffed alongside a machine operator to help with supporting tasks (e.g., pre-aligning pieces of fabric or folding and ironing seams prior to stitching).

Operations are organized in sequence, grouped by segments of the garment, with groups punctuated by feeding points at which bundles of materials for a certain number of segments (e.g., 20 shirt fronts with pockets) are fed. For example, a group of 5 workers assigned to 5 machines will complete 5 operations (sometimes the same operation) to produce left sleeves, another group will do the same for right sleeves, another for shirt fronts with pockets, and another group will work on the collar. Bundles of completed sections of garments will exit segments of the line and be fed into other segments of the line charged with attaching these portions of the garment together until a completed garment results at the end of the line.

2.3 The role of managers

Each production line has a manager (and sometimes 1-2 senior workers doing assistant supervisory tasks and often also serving as feeders). Managers are paid a fixed salary and are eligible to receive a linear productivity bonus above a certain order-specific efficiency threshold. Each manager is assigned permanently to their line and are responsible for several key oversight tasks. First, when a new order is assigned to a line, the line manager must determine how to organize the production process. This decision depends crucially on both the machines and workers available and the complexity of the style of garment to be produced.

Importantly, this initial line architecture (known as “batch setting”) is time consuming and costly to adjust in the middle of producing an order. It is always set at the start of a new order and is rarely and minimally changed for the life of that order to avoid downtime. If productivity imbalances or bottlenecks arise, managers will most often switch the task allocations of some set of

[13] Unit 1: September 2013-February 2014, Unit 8: November 2013-April 2014, Unit 23: August 2013-February 2014, Unit 28: August 2013-February 2014 (all dates are inclusive). While the dates do not fully overlap across units, no trades take place across units such that any non-overlap is not an issue for the analysis. Note that we drop lines that are open only temporarily in cases of excessive demand and lines for which the production data was not recorded consistently over the periods listed above. The workers from these sporadic lines are not counted as workers borrowed on the lines retained in our sample.

workers across machines, or add a helper or second machine to some critical operations, preserving the line architecture otherwise (Adhvaryu et al., 2022a). This recalibration of the worker-machine match (known as "line balancing"), along with some machine-specific technical calibration, is most likely responsible for the marked increases in productivity seen over the life of an order in this setting (Adhvaryu et al., 2023b).

2.4 Absenteeism

On a typical day, 10-11% of workers are absent. Nearly all absenteeism is "unauthorized" – i.e., it is not reported formally to the firm before the date of absence. While the determinants of absenteeism are likely many (and workers are not always forthcoming about reasons why they were absent), anecdotally, common causes include health shocks to the worker or their family members; religious or cultural festivals that require travel to workers' native places, which are often villages in rural areas across India; and temporary economic opportunities that workers perceive as more lucrative than the wages lost due to absenteeism (e.g., harvesting coffee or areca nuts). A loss in wages is the main consequence for workers of taking unauthorized leave; workers are almost never fired given that Indian labor law mandates very high firing costs, particularly for large firms (Adhvaryu et al., 2013).[14, 15]

As we present in section 3.3, lines are on average equally subject to absenteeism. Absenteeism shocks are frequent and large, and can have a substantial negative impact on line productivity. Worker absenteeism creates potential bottlenecks in throughput, if one or more segments on the production line operate more slowly than usual due to lower manpower. The fewer the workers within a given segment, the smaller the "buffer stock" between segments likely is, and thus the higher the probability that one segment must wait for a previous segment's inputs to continue producing.

Managers compensate for manpower shortages in part by reconfiguring worker-operation matches within the line to ease bottlenecks, and in part by asking other lines for workers, as we describe in detail below. The shape this *ex post* recalibration takes, and the resulting need for

[14]We use payroll data to find whether the workers leave the firm at any point between 2013 and 2015, inclusive. We regress the probability of leaving the firm on the number of days the workers were absent during the study period. The regression coefficient is very small and insignificant ($\beta = 0.00014$, SE=0.00009). 64% of workers eventually separate from the firm. The regression coefficient implies that if a worker were to be absent for a whole month during the 6-month study sample they would have a 0.65% higher probability of separating with the firm in the future, which is extremely small.

[15]Despite workers facing a steep cost when being absent in the form of lost wages, absenteeism remains a problem for the firm. We were told that the firm tried different schemes around incentivizing workers to reduce absenteeism in the past without much success. Absenteeism appears to be taken as given by the firm as we have received little traction when we suggested implementing and test policies aimed at reducing it. This is not to say that more cannot be done on that front, which could be valuable as we show in the simulations, but at the time of the study, there was no firm-wide intervention aimed at reducing absenteeism.

additional workers, are best assessed by the line manager himself, as they are most knowledgeable of the style of garment currently being produced and of the comparative advantage of their available workers at the tasks necessary for that order (Adhvaryu et al., 2022a). These differences among otherwise similar workers are not readily evident to managers of other lines. It is infeasible given time and information constraints that managers are able to accurately assess manpower needs of lines other than their own. The complexity of the initial batch setting and the dynamic nature of line balancing thus gives rise to asymmetry of information across managers of different lines as well as limitations to the ability of higher-level managers (such as floor in-charges and factory general managers) to solve the resultant reallocation problems.[16]

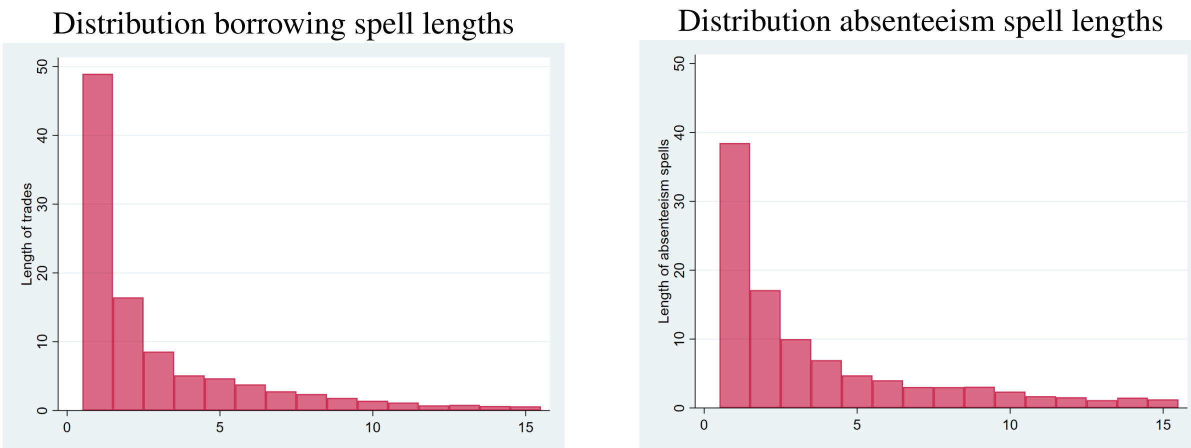
2.5 Allocation of workers across lines

Absenteeism is a key driver of worker movements across lines. Figure 1 plots the distribution of absenteeism and the distribution of borrowing spells. The figure shows that the two closely match providing suggestive evidence that the two phenomena are connected. However, systematic reorganization of workers across lines sometimes occurs to reduce the likelihood of missed deadlines for important buyers and is another important source of movements of workers across lines.

Adhvaryu et al. (2021) show that this systematic reorganization preemptively takes place at the beginning of an order when it occurs. These moves often span for the whole first week of the order (6 workdays) as shown in Figure 2 and are orchestrated by upper management. When upper management is confident that the order deadline will be met, workers are often returned to their original lines. This systematic reorganization of workers across lines to prevent missed deadlines also typically involves high productivity workers from high productivity lines being moved to lower-productivity managers leading to a Negative Assortative Matching (NAM) between workers and managers. Importantly, Adhvaryu et al. (2022a) show that movements of workers across lines initiated by upper management are based on the operation-specific skill of different workers for the critical operations needed for a given order.

[16]This asymmetry is made more difficult to resolve given the short amount of time that the managers have at the beginning of the day to start production. Most workers arrive just before 9 in the morning and production is expected to start promptly at 9 am. Within those few minutes, managers must guess whether the missing workers are really absent or whether they will show up late. The main reason for this pressure to set batches correctly is that momentum builds over the course of the day, and any adjustment comes at the cost of breaking this momentum, which often yields a dip in productivity, and is better avoided (Adhvaryu et al., 2022a).

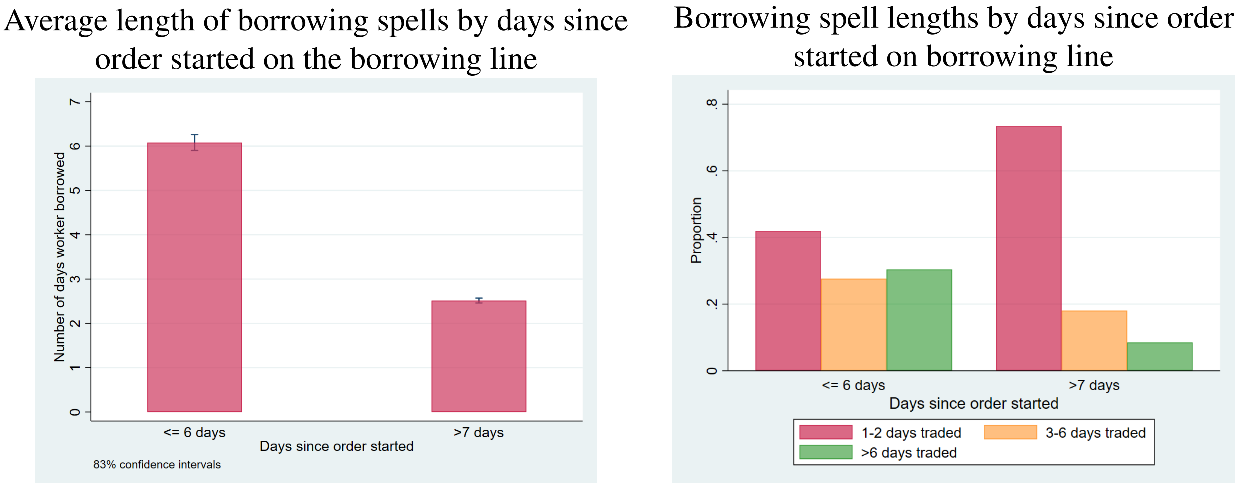
Figure 1: Distribution of trade and absenteeism spells



Note: We calculate the number of days workers spend on another line when traded to that line and plot the distribution across all trades in the left panel. As in the rest of the analysis, when a worker spends more than 15 consecutive workdays on another line, we assume that they have switched home-line and do not count these movements as trades. Workdays span from Monday to Saturday inclusive. In the right panel, we count the number of workdays for which workers are absent for every absenteeism spells and plot the distribution over the same range as in the left panel.

Importantly, each worker is assigned a certification grade in the form of a letter grade which says which operations a worker *can* do. For example, workers with the highest letter grade can do the most complex operations, while workers with the lowest grade can only do the basic ones. Hence, when a line that was producing pants finishes its order and transitions to producing shirts, it needs a worker that is good at sewing shirt collars. The workers that can do these tasks is recorded by the firm. Upper management and line managers can access this information by contacting HR. Therefore, a worker who can sew collars can be taken from a line that, instead, may be transitioning to a garment not requiring shirt collars. While this provides information about the "absolute advantage" of a worker at different operations, we argue below that the absenteeism-driven trades depend on the "comparative advantage" of the workers which varies daily as we explain below. Indeed, the certification grades do not provide information as to which worker is better at a given task even across grades. A worker with the highest grade (worker A) and one with the second-highest grade (worker B) can both do an overlapping set of operations. It could very well be that worker B is better at sewing sleeves than worker A even if the latter has a higher certification grade.

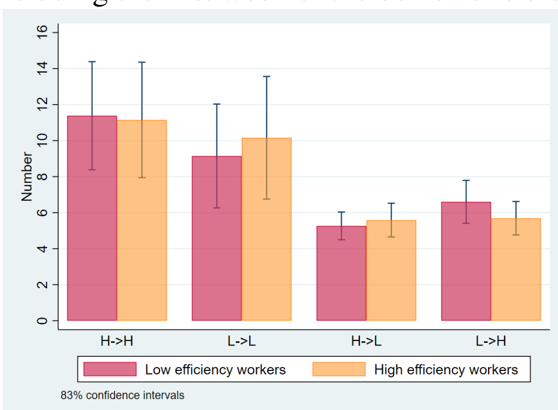
Figure 2: Trade Spells



Note: We plot the average length of trade spells for workers borrowed depending on whether the borrowing line was in the first workweek of an order or not in the left panel. We plot 83.4% confidence intervals. 83.4% intervals that do not overlap indicate that 2 means are different at the 95% level when the samples are independent. At the 95% level and with a large number of observations, $t = 1.96 \approx (\bar{X}_1 - \bar{X}_2)/\sqrt{se_1^2 + se_2^2}$. With common standard errors $\bar{X}_1 - \bar{X}_2 = 1.96\sqrt{2}se = 1.386se$ which corresponds to an 83.4% confidence interval on the normal distribution. In the right panel, we show the distribution of short, medium, and long trades to borrowing lines depending on whether the borrowing line was in the first workweek of an order or not.

We show that this NAM pattern is not driven by the short-term trading spells in response to idiosyncratic absenteeism shocks we study here. That is, we focus on the short-term absenteeism-driven trades which can take place at any point during an order. We document below that these trades are much more consistent with relational contracting than they are with central planning. The reason is that, on any given day, the residual need for different operation-specific expertise will depend on which workers are absent and which operation-specific expertise they contributed to the garment being produced that day on that line. As a result, the comparative advantage of each worker relative to the other workers present on the line varies daily. We argue that this information is more readily observable by line managers who monitor their set of workers daily, but not to other line managers or upper management. For example, workers A and B assigned to the same line may both be good at sewing shirt collars. They both have the same certification grade so it is known that they can both do the task, but suppose that A is better than B at this task, which is information known by A and B's line manager only. Suppose that on day one, A and B are both present and only one worker is needed to sew collars. Worker A can sew the collars and B can be assigned another task, or can be lent out to a line that needs a good collar seamstress. Now, suppose that on day two, A is absent. The line may not be able to afford to lend worker B or assign the worker to another task as B is now the relative best at sewing collars on the line. Suppose that on day three production fell behind, then on day four more collars need to be produced. At this point, the line manager may need to put both A and B on the production of collars. As a result, which of the 50-60 workers on the line can be lent or reassigned to a different task is not easy to assess by managers of other lines or upper management who have less intimate knowledge of these dynamic circumstances. Detailed daily worker-level productivity data used in this research is not available to the managers because these data are recorded *ex post* and require intensive effort in cleaning to be harmonized into a unified database (which we did as researchers for this study).[17] The current data recording system would therefore be ill-equipped to provide real-time information to managers.[18]

Figure 3: Number of high- and low-efficiency workers traded within each type of partnership



Note: Using worker-by-day data, we recover manager (and worker) fixed effects through a decomposition in the spirit of (Abowd et al., 1999). To do so, we regress the log efficiency on unit, year, month, date, and style fixed effects and recover the manager component. We classify managers with a component higher or equal to the median on their floor as high-efficiency managers and those below the median as low-efficiency managers. The manager at the median on odd floors is randomly assigned as a high- or low-quality manager. We split the sample of managers at the median of the managerial quality within units and floors and split the workers at the median within units. This ensures that there are high- and low-quality workers and managers on each floor. We count the number of high- and low-efficiency workers traded from high-efficiency lines to high-efficiency lines, from low-efficiency lines to low-efficiency lines, and from high-efficiency (low-efficiency) lines to low-efficiency (high-efficiency) lines. We compute the average number of workers traded within each type of managerial pair conditional on trading at least one worker and plot these averages when excluding trades going to borrowing lines in the first week of an order in the left panel, and when excluding long trades (longer than 5 days) in the right panel. We plot 83.4% confidence intervals. 83.4% intervals that do not overlap indicate that 2 means are different at the 95% level when the samples are independent.

Figure 3 shows that short-term trades flow between managers of a similar quality level and do not depend on worker quality confirming that these trades are distinct from the systematic reorganization of workers across lines to avoid missed deadlines for important buyers studied in Adhvaryu et al. (2021). In particular, we look at the average number of trades of high- and low-quality workers from high- and low-quality managers to other high- and low-quality managers. We first find that any type of pairs of managers trade high- and low-quality workers with the same intensity. We also find that high-quality managers trade more intensely between one another and so do low-quality managers between one another than pairs of different quality levels. High-quality

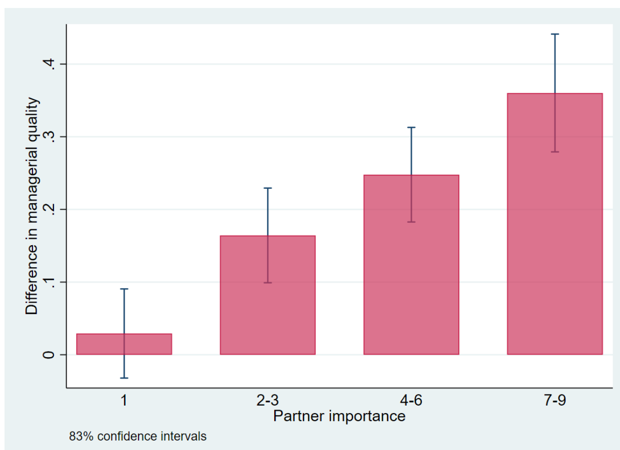
[17]There is no research division at the firm; the data are cleaned quarterly and aggregated to the factory level for the firms upper management to make informed decisions related to factory investment and operations.

[18]Managers sometimes put the number of items produced and daily targets on a white board at the end of their production line, which they update a few times during the day. This practice helps managers keep track of their own production. It is neither mandatory nor made to share information *per se*. While other managers could see this, it remains self-reported line-level production information, rather than worker-level, and importantly, these reports are *after* trades occur.

and low-quality pairs do not differ statistically in their level of trade either. The results are similar if we exclude trades taking place during the first week of the borrower's order or short trades.

We also show in Figure 4 that managers form long-term partnerships with managers of similar quality levels. For each manager, we compute the absolute difference in managerial quality with their first, second, third... most frequent trade partners and plot the average differences by partner importance. We find that the more important are trade partners, the less do the partners differ in quality. In particular, a manager does not statistically differ in terms of quality on average with respect to their most important trade partner while they tend to differ by 0.25 standard deviations from their fourth to sixth most important partners.[19] Finally, we demonstrate in Tables A1 and A2, in Appendix A, that our results are robust to excluding all worker moves which are likely to be centrally coordinated (i.e., trades taking place during the first week of an order and trade spells too long to likely be responses to idiosyncratic absenteeism shocks).

Figure 4: Partnerships and managerial quality



Note: Using worker-by-day data, we recover manager (and worker) fixed effects through a decomposition in the spirit of (Abowd et al., 1999). To do so, we regress the log efficiency on unit, year, month, date, and style fixed effects and recover the manager component. We classify managers with a component higher or equal to the median on their floor as high-efficiency managers and those below the median as low-efficiency managers. The manager at the median on odd floors is randomly assigned as a high- or low-quality manager. In particular, we split the sample of managers at the median of the managerial quality within units and floors such that there are high- and low-quality managers in each unit-floor. We look at every manager's first, second, and third most frequent partners and compute the absolute difference in managerial quality. We plot the average absolute difference in managerial quality by the importance of partners expressed in standard deviations from the mean managerial quality across all managers. We plot 83.4% confidence intervals. 83.4% intervals that do not overlap indicate that 2 means are different at the 95% level when the samples are independent. Manager A can have manager B as their most important partner, but manager A may not be manager B's most important partner. Hence, for the first bar for example, we compute the average difference in managerial quality between every first partner.

2.6 Cooperation between managers

In practice, when facing larger absenteeism shocks that can be mitigated via line reconfiguration alone, managers often ask to borrow workers from fellow managers' lines. Managers "lend" workers knowing that they also face the prospect of absenteeism shocks in the future, and expecting that the favor of lending workers will be returned at that time. Interviews with managers in the factories

[19]In Figure 4 we obtain the same manager effects used in Figure 3 and split again at the median within unit and floor such that there are high and low-quality managers in each unit-floor.

under study regarding strategies for addressing absenteeism were quite revealing. One manager reported that "when facing absenteeism, I will try to get workers from other managers by talking to them directly." Another said that "managers form relationships mainly through being on the same floor and understanding that cooperation is mutually beneficial." This *quid pro quo* in essence defines the relational contract we empirically study in this paper.

It is worthwhile noting that this cooperation is likely very difficult to organize or impose at higher levels of management, and impossible to formally contract on via existing organizational structures, due to the private information each manager has about their own worker requirements given the style, workers present, and possible recalibrations of worker-operation matches, for any given set of realizations of absenteeism shocks across lines. This means that line managers rely on their relationships as a primary safeguard against the deleterious effects of absenteeism on productivity. Moreover, cooperating can entail a contemporaneous loss for the lenders. Indeed, managers receive a base wage and are entitled to a daily bonus pay if they produce above a certain daily threshold representing less than 10% of their total daily compensation.[20] There are no direct monetary incentives for lending workers. Hence, by lending workers managers may realize this bonus with lower probability in the current period. This pay structure is not inherently designed to foster cooperation and may indeed discourage lending. However, managers may still benefit from trading in the long run. We show in subsection 3.6 that trading is highly symmetric in that managers repay the workers they borrow by lending back to their partners. This suggests that managers are willing to lend despite the implicit (contemporaneous) disincentives created by the pay structure. Such systematic and symmetric repayment of borrowed workers would be inconsistent with centralized planning of worker moves.[21]

3 Data and empirical facts

To start our investigation into relational contracting, we document the daily flows of workers between pairs of line managers. In this section, we describe the data we use and report empirical facts depicting the importance of absenteeism and the nature of cooperation among managers. The

[20]Workers are also entitled to a productivity bonus when the whole line exceeds the daily production target, but it similarly represents a small percentage of their daily pay. Nevertheless, this incentive structure may make workers, especially high-productivity workers, reticent to be traded to a line with higher absenteeism. We find that high-productivity workers are indeed traded less often in Appendix H which could be consistent with this idea. However, to our knowledge, workers have little say in where they are assigned. Even if more productive workers had more power in whether to agree to move lines, we find that these workers are still traded even if marginally less often, and tend to go to the lines of their manager's main partners while lower-productivity workers are traded less selectively. All of these patterns are still consistent with the relational contracts we propose in this study.

[21]In Appendix B, we also show that whether managers are on the same factory floor and the physical distance between them if on the same floor are uncorrelated with their demographic similarity, indicating that upper management does not appear to be placing demographically similar managers nearer to each other in an effort to foster trading relationships.

data shows that absenteeism shocks are large, frequent, and idiosyncratic. Managers appear able to deal effectively with absenteeism up to roughly 9%; past this point, overall efficiency begins to suffer. Managers borrow workers from other lines to cover for their own missing workers, but this cooperation appears somewhat limited. Managers do not trade with all possible partners, such that many productivity-enhancing trades go unrealized.

3.1 Key variables

For each production day, we observe the identifier of each worker and their average hourly productivity on the line to which they were assigned for the day. Each line has a permanently assigned manager as well as a set of workers assigned by default to that line. Each worker's default assignment, or "home line," is easily determined in the data as the line on which the worker spends the vast majority of their time. The data show that workers spend on average more than 90% of their days on one primary line over a given 3-month period, for example.[22]

In response to absenteeism of home-line workers on a given day, line managers can borrow workers from other lines and/or lend some of their own home-line workers to other lines. We know whether each worker is absent on a given day by whether their productivity is recorded at all, irrespective of the line on which they appear to be working. Accordingly, we define the percentage of absenteeism as the number of the home-line workers of a line that did not have any recorded productivity on a given day divided by the number of home-line workers usually available to that line. That is, absenteeism for a manager on a given day is the proportion of their own workers that did not show up to work that day, and not the proportion of how many of their own workers are not present on their line. The definition we use is independent on whether the workers were traded or not that day, simply whether they were present or not. For example, if a line has 50 home-line workers and 5 are not working on any line in the factory on a given day, then we calculate the absenteeism of that line as $5/50 = 10\%$.[23] Lines can differ in size across units, mainly driven by the configuration of the factory floor and the types of garments the factory makes. As a result, one missing worker may not affect all the lines the same way; while 1% of workers absent is more likely to reflect a similar magnitude of shock. For this reason, the percentage of available workers absent is our preferred measure and allows us to pool the results easily in figures and regression analyses.

We are also able to identify which workers were borrowed from another line. That is, if a worker has recorded productivity for a given day on a line other than their current home line, we

[22]Over 80% of workers keep the same home line throughout the span of the data and another 15% of workers see a single permanent change in their home line. We provide more detail on the determination of workers' home line in Appendix J.

[23]We allow the pool of available home-line workers to change over time, to reflect both more permanent reassignments to new home lines as well as worker attrition from the factory. To account for turnover, we assume that workers who did not show up for two consecutive weeks or more are no longer part of a manager's pool of available home-line workers.

know that the manager of that line has borrowed them from their home line manager for the day.[24] With these measures of absenteeism and borrowing and lending of workers in hand, we construct our main dyadic dataset by pairing each production line to their potential partner lines.[25] In addition to the absenteeism of each line in the pair, we are interested in the impacts of physical distance between lines and the maturity of relationships between managers of two different lines on whether and how many workers are exchanged. We measure relationship maturity by the cumulative number of days two lines have exchanged workers up to the observation date.[26] Distance is measured in feet between two production lines on the same floor.[27]

In addition to physical distance, we also look at the effect of the demographic (dis)similarity between pairs of managers (via gender or education differences, for example). In Table B3 of Appendix B, we present the demographic composition of the managers in our sample. For each demographic variable we show the most common category across managers in the sample.[28] Most managers are male (88%) and Kannada-speaking (75%). Most identify as Hindu with roughly 40% belonging to the "general" caste category. More than 40% have at least passed the 10^{th} grade and more than two thirds were born in the state of Karnataka, but outside the metro area of the capital, Bengaluru.

[24]Note the productivity of all workers is reported regardless of the task they do.

[25]In other words, if manager *i* has 10 potential partners, the first row lists the number of workers borrowed by line *i* from the first partner, the second row lists the number of workers line *i* borrows from the second partner, and so on until the 10th partner. We define the set of potential partners for a given line as every other line on the production floor. There is no explicit policy stopping managers from borrowing workers across floors in units that have multiple floors. However, in practice trade across floors rarely occurs.

[26]We explore cumulative number of workers traded between two lines to date as an alternate measure, and find no meaningful differences in results.

[27]We do not have a measure of distance for lines on different floors, but given the rarity of trades across floors we ignore these trades in our analysis.

[28]The manager identities and demographic data is obtained from a one-time survey of the managers. Accordingly, we cannot observe managers moving across lines over the study period, but were told by the firm that such moves are extremely rare if they happen at all, especially over a short period like the 6-7 month spans we study.

Table 1: Summary statistics at the line level

Variables	Mean/(S.D.)
Number of home-line workers assigned to the line (absent or not)	56.27 (16.49)
Number of workers present on the line (home-line workers or not)	50.80 (18.89)
Number of home-line workers present in the unit	50.80 (16.69)
Percentage of home-line workers present in the unit	89.09% (12.92)
Number of home-line workers absent	5.74 (7.02)
Percentage of home-line workers absent	10.90% (12.92)
Distance in feet from other lines	9.37 (5.88)
Number of line by day observations	13,524

Note: The data includes daily worker-level data from 4 garment factories spanning 6-7 months for each factory. Our sample consists of 73 sewing production lines. A typical production line has between 50-60 workers which usually corresponds to one worker per machine. Each production line has a line manager (and sometimes 1-2 senior workers doing assistant supervisory tasks and often also serving as feeders). Absenteeism is defined as the difference between the number of home-line workers present in the factory on a given day and the total number of home-line workers available. Distance is measured in feet between two production lines on the same floor.

In Table 1, we present summary statistics of key variables at the line level. Lines typically have 56 home-line workers. On average 10.9% of home-line workers are absent on any given day corresponding to 5 to 6 workers absent. On the factory floor, lines either run parallel or end-to-end or both. Factories have typically 17-18 lines (mean 17.5, SD 3.42) spread across 3-4 floors (mean 3.75, SD 1.71) with roughly 5-6 lines on each floor (mean 5.23, SD 1.82). Lines are on average 9 to 10 feet from their potential partners on the factory floor.[29] Turning to the workers, we find that, over the span of the data, approximately half of the workers are traded to other lines at least once. About 30% of them are traded multiple times, with 23% being traded two to five times (see Figure B1).

3.2 Absenteeism and line productivity

We begin our presentation of empirical facts by documenting the relationship between absenteeism and productivity at the line-day level. In the garment industry, efficiency is the global standard to measure productivity. The target quantity of a specific garment to be produced is determined from a measure of garment complexity called the standard allowable minute, or SAM. SAM is the ideal amount of time measured in minutes it should take, in an optimal setting, for a

[29] Our distance measure attempts to capture as well as possible the layout of the factory floor. The distance is measured between the two closest ends of each line for end-to-end lines. For lines running in parallel, the distance is measured from the center of each line.

master tailor to produce one unit of a certain style of garment (e.g., one men's shirt).[30]

For example, it should take 30 minutes to produce one style of men's shirt if it has a SAM of 30. If the production of this shirt is split into 60 operations, the average SAM per operation would be 0.5 (i.e., each operation should take 30 seconds to complete on average), with SAM for each specific operation adjusted to reflect the complexity of the operation. Workers doing a specific operation with SAM of 0.5 should complete $60/0.5 = 120$ operations per hour.[31] The efficiency of a worker (per hour) is simply the number of operations they are able to perform per hour divided by the target number of operations per hour given by the SAM. If a worker is producing left sleeves and has a target of 120 sleeves per hour under the SAM, but produces 60 sleeves per hour on average in the course of a day, then their efficiency is 50% for that day.

To calculate daily efficiency of a line, we simply average the efficiency of the workers working on this line that day. In our data, the average hourly efficiency at the line level is 49.09% (SD 15.85%). Realized efficiency is far from 100% because the SAM reflects production in an optimal environment. Indeed, the SAM measure does not account for the fact that workers may become less productive as the hours go by or that machines may break and that bottlenecks may arise.

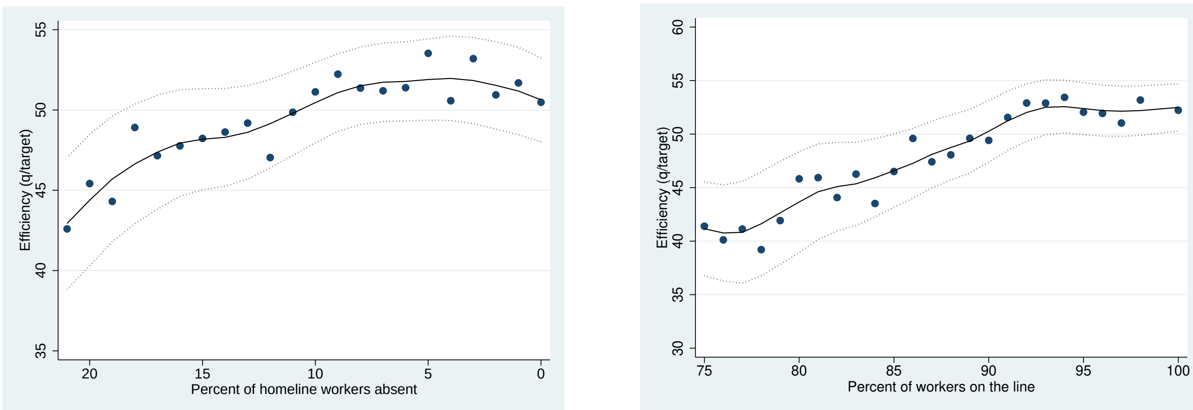
Figure 5, panel (a), plots line average efficiency against the percentage of home-line workers absent, showing a decreasing and concave relationship. That is, absenteeism has little effect up to 9 or 10%, but has a large negative effect on efficiency thereafter. Average efficiency drops from above 50% at less than 10% absenteeism to below 45% at 20% absenteeism. While absenteeism captures the proportion of a manager's workers that showed up for work regardless of which line they work on that day, efficiency of the line is measured after any realized trades. We might want to see this relationship before any trading occurs, but restricting the sample based on high- or low-realized trading would, of course, conflate any inability to borrow with unobservable true need for borrowing. Figure 5, panel (b), on the other hand, plots the average efficiency of the line against the number of workers working on the line that day (whether or not this line is their home line, i.e., including realized trades) as a percentage of the line size (given by the number of home-line workers assigned to this line if they were all present). We can see that when a line has approximately 93% or more of its designated number of workers, efficiency remains relatively constant at around 52%.

[30] SAM is a standard measure used in the garment industry that is drawn from a database of industrial engineering standards that documents the estimated time each operation should take and the operations that are estimated to be required to produce one unit of a garment of a certain style. In reality, workers on a line producing a men's shirt do not produce one shirt at a time, but produce buffer stocks of certain parts of that shirt (sleeves, collars, torsos,...), which are then assembled by separate workers. In addition, workers may be absent, their productivity may decrease from one hour to the next, machines may break, etc. Hence, the number of operations needed and the time needed for each operation may differ from what the SAM measure would suggest.

[31] If another operation takes longer than average and has a SAM of 1 for example, then workers doing this operation are expected to do $60/1 = 60$ operations per hour.

Figure 5: Average line-level efficiency...

(a) ...per percentage of "home line" workers absent (b) ...per percentage of workers working on the line



Note: In the first panel, we compute the average efficiency of the workers on the line by percentages of absenteeism. Scatter depicts the mean within integer bins of absenteeism; solid line depicts a nonparametric fit; and dotted lines represent the 95% confidence interval. We restrict focus to days in which lines have 25% absenteeism or less as larger absenteeism is rare. In the second panel, we plot the average efficiency of the line against the percentage of workers working on the line. Percentage of workers on the line is calculated relative to the number of home-line workers assigned to this line. We ignore rare cases when less than 75% or greater than 100% of the number of assigned home-line workers are present. Scatter depicts the mean within integer bins of absenteeism; solid line depicts a nonparametric fit; and dotted lines represent the 95% confidence interval.

Taken together, the figures show that large absenteeism shocks appear to be detrimental to line productivity, but that fairly small shocks have little impact. This could reflect both the shape of the production technology as well as manager ability to make do with the available workers (i.e., set the batch at the start of the order to accommodate future absenteeism shocks and perform worker-task reassignments to mitigate potential losses due to absenteeism shocks). In either case, the figures show that an average line experiencing little to no absenteeism on a particular day (e.g., more than 93% workers present) may actually be able to spare some workers without forfeiting productivity; while a line experiencing a large absenteeism shock (e.g., less than 90% workers present) could benefit greatly from being lent those spare workers.

3.3 Absenteeism shocks are large, frequent, and idiosyncratic

The potential for gains from trade of workers between lines with high and low absenteeism on a given day depends crucially on how frequently lines experience absenteeism shocks large enough to impact productivity and how likely it is that some other line on the floor is experiencing much less absenteeism on the same day. To investigate this, we study the distribution across days of the percentage of lines in the sample that experience absenteeism of at least 10%. We do the same for shocks of at least 15%, 20%, and 25%. We find that large shocks are quite frequent. Indeed, on any given day, roughly 35% of lines on average experience an absenteeism shock of at least 10%; roughly 17% of lines (or more than 1 line on a floor containing 6 lines) experience a shock of at least 15%; 9% of lines experience a shock of at least 20%; and 6% (or 1 line in a factory with 16 lines) experience a shock of at least 25%, or nearly 14 out of 55 home-line workers absent (see Figure C1 of Appendix C).

We also look at the average within-day correlation in absenteeism of different lines across units, within units, and within floors. While the correlation increases slightly across specifications, the magnitudes all remain small. The within floor-day correlation, most relevant for determining opportunities for trade among line managers, is only 0.145. This confirms that, since absenteeism shocks are largely uncorrelated even for lines on the same floor, managers could potentially mitigate the burden of absenteeism by borrowing workers from lines experiencing less absenteeism on a given day (see Table C1).

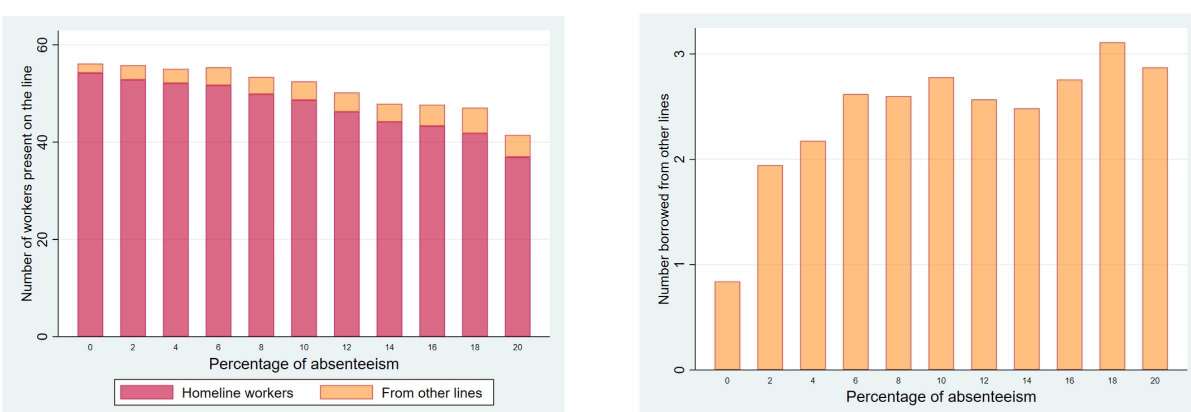
3.4 Managers borrow workers to mitigate the impact of absenteeism

Figure 5, panel (a), indicates that managers should want to borrow more workers as their absenteeism increases, and the lack of correlation between absenteeism shocks across lines reported above suggests that some other lines on the floor should likely be in the position that day to spare some workers. Indeed, Figure 6, panel (a), shows the number of workers borrowed by a line grows with that line's percentage of absenteeism. Due to the shape of the relationship between efficiency and the percentage of workers actually working on a line (Figure 5, panel (b)), one would expect that managers desire to borrow would be low at lower level of absenteeism, and high at higher level of absenteeism. In other words, intensity of borrowing against absenteeism should have an increasing and potentially convex shape.

Figure 6: The number of workers borrowed...

(a) ... increases with absenteeism

(b) ... increases up to a certain point



Note: In the first panel, the full bars represent the average number of workers on the line for different percentages of absenteeism across the lines in our sample. The darker bars indicate the average number of home-line workers on the line and the paler bars represent average number of workers borrowed. In the second panel, we show the average number of workers borrowed across lines by percentage of absenteeism. The bars here are the same as the paler bars in the first panel.

However, Figure 6, panel (b), which zooms in on the number of workers borrowed for each level of absenteeism, shows that the relationship between the two is increasing, but concave.[32] A likely explanation is that desire to borrow does not translate fully into the realized number of workers borrowed. That is, this evidence is consistent with line managers facing difficulty in borrowing a large number of workers from any one partner or borrowing from many partners at once.

At relatively low levels of absenteeism, a manager may need 1 or 2 workers to return to full manpower. On the other hand, a line with 60 machines and 15% absenteeism would need to borrow as many as 5 workers to get back to peak efficiency. While it may be likely that a partner will be willing to part with a few workers, it is unlikely to find a partner willing or able to part with a larger number of workers, given that no manager would want to relinquish so many workers such that the percentage of workers actually working on their line falls below 93% (as depicted in Figure 5, panel (b)).

Because managers can only ask so much from their partners, we see that the average number of workers borrowed is concave in absenteeism, reflecting the duality between their own need and the lending capacity of their partners. On the other hand, a manager could borrow from several partners each in the position to share a small number of workers, which they are sometimes able to do. However it is not always the case, as we show below, since line managers actively trade with only a few other managers that may not always have workers to spare, consistent with partnerships being costly to establish and maintain. Note that there is heterogeneity in the number of workers borrowed. Since managers do not always borrow, Figure 6, panel (b), may give the false impression that managers always borrow very few workers. The unconditional average number of workers borrowed is 1.9 (SD 2.95) with the 5^{th} and 95^{th} at 0 and 7 workers borrowed respectively. Conditional on borrowing, managers borrow on average 3.38 workers (SD 3.24) with the 5^{th} and 95^{th} corresponding to 1 and 9 workers respectively.

3.5 Absenteeism affects productivity despite (limited) borrowing

Next, we investigate whether these apparent limitations to borrowing in the presence of large absenteeism shocks translate into limitations on the ability to mitigate the impacts of absenteeism on productivity. In Table D1 of Appendix D, we regress line-level efficiency on *home line* absenteeism, noting that observed efficiency is realized net of any borrowing. Large common absenteeism shocks across the factory floor would generate impacts on productivity; however, if managers are able to fully smooth the effect of their idiosyncratic absenteeism by way of borrowing workers, a manager's own absenteeism should not impact the line productivity after controlling for aggregate absenteeism.

[32] Managers sometimes borrow at low-absenteeism level when they have critical operations to fill. Some garments may require a specialized task that only a few key workers can do. Therefore, lines may borrow a specialized worker every now and then to fill this operation that none of their workers can do.

We find that even after accounting for most aggregate absenteeism shocks at the factory floor level by way of a broad array of fixed effects, a line's idiosyncratic absenteeism still impacts its productivity. For example, a 10 percentage-point increase in absenteeism decreases efficiency by roughly 4 percentage points. That is, risk-sharing among managers appears far from perfect.[33]

Some factors may jointly affect absenteeism and efficiency. For example, previous studies from this empirical context have shown that efficiency is impacted by temperature (Adhvaryu et al., 2020) and air pollution (Adhvaryu et al., 2022a). It is also possible that on excessively hot or polluted days, more workers decide to stay home. Similarly, a manager may attempt to increase their line's productivity by treating workers harshly or react to poor productivity by scolding workers, driving up absenteeism. In order to account for such potential endogeneity or reverse causality, we instrument for absenteeism using the number of home-line workers from a state with a major religious festival on a given day in Table D2. Through a series of analyses in Appendix D, we show that the negative effect of absenteeism on productivity is robust (and indeed statistically equivalent) when using the instrumental variable (2SLS) strategy.[34] Our instrument leverages the number of home-line workers that are from a state with a recognized religious festival on a given day which has a strong incidence on absenteeism. The IV strategy is able to account for contemporaneous events affecting both absenteeism and productivity such as the ones presented above. The IV would not be able to address endogeneity in the case where a manager was able to predict future absenteeism based on future festivals, and adjust production accordingly that day. This, however, would be extremely hard to do since workers on a given line are from many different states where different deities are worshiped with various degrees of intensity in festivals that very both in dates across states and across years within states. On any given day, about 11% of a manager's available workers are from a state with a festival that day with a standard deviation nearly 3 times as large (SD 30%). Also, a given festival in a given year caters to on average 4% of any manager's available workers with a standard deviation also 3 times as large. Hence, even if a manager was able to predict that absenteeism is likely to be more pronounced a few days ahead because of larger festivals like Diwali, it would be very hard to anticipate *how much* absenteeism there will be given overlapping festivals often happening concomitantly across the country. We also check that the incidence of absenteeism shocks is balanced across lines and managers of varying productivity level using manager fixed effects estimates obtained from an AKM specification (Abowd et al., 1999). Moreover we include line fixed effects in all regressions to account for differences in demographic characteristics and

[33]We also run an analogous regression with the most stringent possible fixed effects (line, unit, and floor by date) to fully account for daily floor-level shocks. The point estimate is -0.452 (SE=0.043 when clustering at the line level and SE=0.039 with line and date clusters). Hence, the coefficient is is still highly significant even when accounting for daily floor-level shocks, further confirming that absenteeism is not smoothed perfectly on average.

[34]The instrument and the procedures are detailed in Appendix D. As mentioned in the analysis section, we can't use the instrument in the dyadic analysis given the nonlinear nature of the regressions, but the results presented above indicate that absenteeism episodes can indeed be considered as exogenous shocks.

skills of managers as well as the size and composition of their pools of home-line workers.

Using a subset of days for which we have worker bonus payment data and the same IV strategy mentioned above, we find that workers have a 25% chance of receiving a daily productivity bonus on average, but this probability falls by 2.1 percentage points for every percentage point increase in absenteeism (or roughly 14 percentage points for a 0.5 SD increase in absenteeism).[35] This result shows that the negative impact on productivity of absenteeism not only affects the firm, but also reduces the welfare of the workers who show up for work. It also reinforces that managers, who are also eligible for the productivity bonus payment, have an incentive not to lend workers on any given day suggesting that, if they are still willing to lend workers, the value of being able to borrow workers in the future must be large.

3.6 Many potential trading partnerships are left unrealized

The previous section indicates that although managers exchange workers to cope with absenteeism, the trades are not sufficient to completely mitigate the impacts of absenteeism on productivity. We next document that managers seem to forego many potential partnerships. If we rank a manager's partners by the number of times they have exchanged workers over the span of the data, we find that 72% of all workers traded are exchanged with the three most frequent partners.

Moreover, managers are only ever observed (in the span of our data) forming a few trading partnerships. Under the definition that managers formed a partnership if they ever exchanged at least 2 workers a month for 4 months (consecutive or not), managers form 2 to 3 partnerships on average. If we assume instead that managers form a partnership if they ever traded and borrowed one or more workers between one another over the span of the data, we would conclude that managers form on average at most 5 partnerships. There are on average 20 to 22 managers per unit. Therefore, managers forgo approximately 15-17 partnerships on average in the most "generous" definition of a partnership. If we ignore incidental trades, managers forgo 17 to 19 active partnerships on average. There are no explicit reasons restricting managers from trading across factory floors. Nevertheless, they very rarely do so perhaps because they can't maintain partnerships if they can't monitor their partners' lines. If we believe that relational contracts are hard to maintain across floors, managers still forgo at least half of partnerships on their floor which have on average 6 production lines, under the more realistic definition of partnership.

Next, we study the intensity of trades between partners. In particular, we rank the partners of each manager based on how often trades occur in the pairs and investigate the percentage of all workers exchanged going to each partner. We find that the intensity of trade is not uniform across partners. Indeed, on average, 40% (20%) of all workers borrowed come from the most important

[35] The average unconditional (i.e., including days without bonuses coded as 0s) daily productivity bonus is approximately 10 rupees and it falls by 0.2 for every percentage point increase in absenteeism.

partner (second most important). Moreover, the percentage of workers borrowed falls rapidly with the rank of the partner clearly indicating that managers maintain active partnerships with only a few other managers. The same is true for the percentage of workers lent. We find that relationships are symmetric in that a manager will borrow the same number of workers that they will lend to a given partner on average. That is, managers pay back their partners when they borrow from them by lending them workers at a later time (see Figure B2 of Appendix B).

Managers tend to exchange workers with lines that are within a short distance on the factory floor. We find that 72% of the workers ever traded are with lines that are within 20 feet. We also find that managers tend to trade with managers that are similar to them in terms of demographic characteristics.[36] For example, managers conduct nearly 80.2% of their trades with managers of the same gender. If workers were randomly assigned by, say, a central planner, we would expect that only 66% of trades would happen between managers of the same gender given the gender composition of the different units.

We also look at the interquartile range of the daily number of worker traded by pairs of lines by distance bins between the lines and by the maturity of the relationship as measured by the cumulative number of days they have traded at least one worker. We find that distance is negatively related with trade, while maturity is positively related. Both distance and age appear to have a roughly linear relationship with trade (see Figure B3).[37]

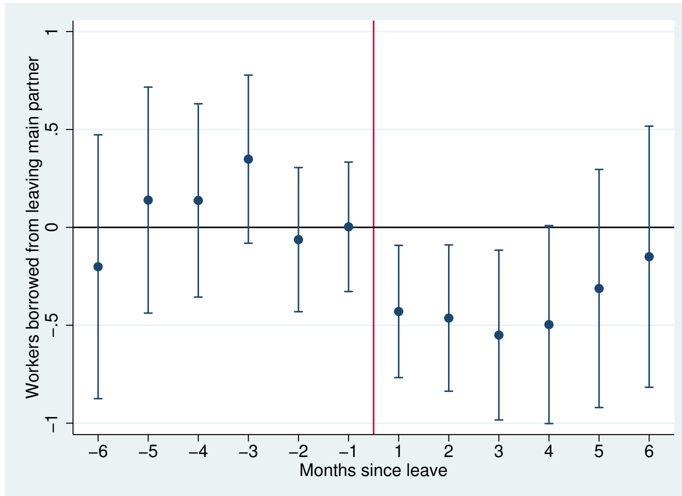
3.7 Trade breaks down when an important partner leaves

If the trade patterns observed indeed stem from relational contracting as we hypothesize, then we should expect that relationships break down when a partner leaves. On the other hand, no break would be expected if trades are planned centrally such that the identity of the lending line's manager is irrelevant. In Figure 7, we plot the coefficients from an event-study regression of the number of workers borrowed from a line's main trading partner before and after the partner line's manager leaves. We focus on the borrowing of lines which themselves do not experience any turnover to make the exercise easily interpreted and restrict attention to cases in which the main trading partner was stable over at least the one full month prior to the departure of the partner line's manager.

[36] Of course, unobserved similarities between lines could account for some of the trades. For this reason, we include line fixed effects in the main analysis.

[37] Note that the relationships are virtually identical if we plot the number of workers borrowed or the number of workers lent on the vertical axis rather than the sum of the two. This is consistent with Figure B2 that suggest that managers repay the workers they borrow.

Figure 7: Workers borrowed from main partner lines with a departing manager



Note: We compute the average number of different workers borrowed weekly by lines without managerial turnover from important partners with a leaving manager six months before and 6 months after the leave. We regress the number borrowed on dummies for every month before and after the manager leaves and include unit, year, month, and lines fixed effects. The first month before (after) the manager leaves is composed of the first (last) three weeks of that month. The two weeks during which the manager separation occurs are the excluded dummy. We know that the separation occurs within those two weeks, but not the exact date. We plot 95% confidence intervals.

Figure 7 shows that before the manager separation occurs, trade is flat or weakly increasing, followed by a sharp reduction in trade when the manager of the main trading partner line leaves and a gradual recovery thereafter. It takes at least 3 or 4 months for trade to recover. Such a break in trade is consistent with relational contracts, as it is less likely that managerial turnover would affect how a central planner moves workers around in response to absenteeism.[38, 39]

4 Empirical tests

In this section, we show more formally that managers respond to absenteeism shocks by lending and borrowing workers in a manner consistent with relational contracting. Most of the seminal

[38]When including a spline for the time to separation of a manager in our main regression, the time until separation is insignificant indicating that managers do not change their trading behavior prior to the separation as Figure 7 suggests.

[39]*A priori* this pattern could also be explained by the fact that newly hired managers are less productive initially and can't afford to lend workers. However, we find that the relationship between efficiency and workers on the line depicted in Figure 5(b) is statistically the same for managers hired more than 6 months prior to the date of observation than it is for managers hired for less than 6 months (not shown). In particular, the relationship is flat for both types of managers above 93% of workers on the line. This is consistent with the results from (Adhvaryu et al., 2022a) showing that tenure has little impact on productivity differential across lines, but has a stronger impact on the speed at which managers reach peak productivity within the life of an order. We find that the main results are not meaningfully impacted when controlling for days spent on an order (see Tables2 to 4) or when including a dummy for weather manager is new or not. Note that the production function in the simulations section is also virtually unchanged when controlling for the number of days since the beginning of an order. Taken together, these results indicate that learning-by-doing has little effect on observed trading patterns. Hence, we believe that the diminution in trade between lines after a manager leaves is indeed more likely due to the breakdown of relational contracts.

models of relational contracts involve a transfer of utility between risk neutral agents; while in our setting managers transfer workers who are inputs in a concave production function. In Appendix E, we propose a simple framework that better represents the context at hand, drawing elements and intuition from many of the established models of relational contracting (Coate and Ravallion, 1993; Halac, 2012; Levin, 2003; MacLeod and Malcomson, 1989; Malcomson, 2016; Yang, 2013).

The model is designed to match the qualitative features of the context described at hand and delivers predictions similar to the models above. This shows that the key insights of the relational contract literature carry through in our setting. In particular, the model predicts that in a stationary relational contract the number of workers borrowed by manager i from manager j, (1) decreases as i's state (i.e., increases with absenteeism on i's line) improves (or i's absenteeism worsens) relatively to j's, and (2) increases as the transaction cost between i and j decreases; (3) moreover, it follows that as transaction costs decrease, the frequency of transfers between i and j increase. On the equilibrium path, as the maturity of the relationship (the cumulative number of transfers between managers i and j) increases, (1) the amount borrowed by manager i from manager j also increases and, (2) the frequency of transfers between i and j increases.

4.1 Empirical strategy

As discussed in section 3, the dataset we use to test the predictions consists of a dyadic panel of all potential manager partnerships on a production floor for every production day.[40] The predictions suggest that this trade decision depends on the demographic similarity of the managers and the physical distance between the production lines (transaction cost). In this sense, our empirical setup is similar to the canonical gravity model, which has the basic conclusion that trade between two countries is inversely proportional to their distance (Anderson, 2011; Anderson and Van Wincoop, 2003; Chaney, 2018; Donaldson, 2018). We follow this literature in estimating the following log-gravity count equation derived from the model:

$$\begin{aligned}\theta_{ijuft} = \alpha + \beta_1 \frac{(\%Abs_{iuft} - \%Abs_{juft})}{2} + \beta_2 ln(Maturity_{ijuft}) + \beta_3 ln(Dist_{ijuf}) + \beta_4 Gender_{ijuf} \\ + \beta_5 Education_{ijuf} + \beta_6 ln(Age\,diff_{ijuf}) + \beta_7 ln(Experience\,diff_{ijuf}) + \Phi + \varepsilon_{ijuft}, \qquad (1)\end{aligned}$$

where the subscript i refers to a given manager and j to a potential partner on the floor. Subscript u indicates the unit or factory, f the floor within the factory, and t indicates the date.[41] Our dependent

[40] As we note in section 3, negligible trade occurs across floors; accordingly, we focus on pairs of managers located on the same factory floor. As such, the distance variable is defined as the number of feet between two lines on a factory floor.

[41] We abstract from capital input and material input choices: the machines and materials needed to produce a given style are decided at the firm level and are readily available to production lines, such that conditional on style, there is no variation across production lines in the quantity and quality of machines and materials available. Therefore, we note that the identification issues around the endogenous choice of capital and materials highlighted by the literature on production function estimation do not apply in this case (Ackerberg et al., 2015).

variable, θ_{ijuft}, is the number of workers borrowed by manager i from manager j on floor f in factory unit u on date t. In line with the model, our main independent variable is the average difference in absenteeism between manager i and its partner j on date t. We expect that the number of workers borrowed is larger the worse is i's state compared to j's state.[42] We also include the natural log of the maturity of the relationship between the managers, the natural log of the distance between their lines, and binary variables for whether the managers are of a different gender and have a different level of education as well as the natural log of the (absolute) difference in age and experience of the managers in managing their current lines, which are proxies for so-called identity-based distance.[43, 44] In some specifications we include the natural log of the number of days since i's order started to account for learning-by-doing.[45]

In addition to physical and demographic distance between managers, another dimension that might determine heterogeneity in trading responsiveness (both borrowing and lending) is each managers' quality as studied in Adhvaryu et al. (2023b). We document in Figure D2 that absenteeism is balanced across managerial quality and we include line fixed effects (as discussed further below) to ensure that manager quality differentials are not driving our results on trading partnerships. Nevertheless, we do investigate in additional results below the degree to which different dimensions of managerial quality predict trading activity.

The matrix Φ corresponds to varying sets of cross-sectional and temporal fixed effects depending on the specification used. In particular, we include unit, line i and line j fixed effects as well as year, month and day of the week fixed effects to account for common seasonality in absenteeism across managers. Note that even with the most stringent set of fixed effects, 70% of the variation in the distribution of daily line-level absenteeism remains. For all regressions, we report three types of standard errors. First, we cluster at the manager pair level. These standard errors are reported in parentheses (163 clusters). Second, we use a two-way clustering strategy with one cluster for the manager pair (163 clusters) and one cluster for the date (314 clusters). These two-way-clustered standard errors are reported in square brackets. Finally, in curly brackets, we report two-way-clustered standard errors with one cluster for each manager in the pair (73 clusters each). The different approaches to clustering employed correspond to the most common strategies used when dealing with dyadic data.

[42] Our model yields prediction for cases where i's absenteeism $\geq$ j's absenteeism. In our main results we consider only theses cases. In Appendix G, we show that the results hold if we include cases where j's absenteeism $>$ i's absenteeism.

[43] Managers have a similar level of education if they fall in the same category as defined as follows: (1) did not pass 10th grade, (2) passed 10th grade, (3) completed high school (passed 12th grade), or (4), have a bachelor's or higher degree.

[44] Recall that the age difference and the difference in experience managing the line are not correlated $\rho = 0.0446$.

[45] We take the natural log of the variables listed above and add 1 in order to not exclude cases where the variables are equal to 0.

Since the left-hand side is the count of the number of workers borrowed and that many partnerships are left underutilized, estimating this equation by OLS is known to yield inconsistent estimates. Instead, following the trade literature, we estimate the model using Poisson Pseudo Maximum Likelihood, or PPML (see, e.g., Bryan and Morten (2019); Costinot et al. (2019); Silva and Tenreyro (2006, 2011)). Count models with instrumental variables in addition to fixed effects are known to suffer from incidental parameter problems and have been shown to be inconsistent (see Cameron and Trivedi (2013) and Beghin and Park (2021)). Therefore, we do not use the instrument directly in these dyadic gravity-style regressions. Rather we perform a series of checks presented in Appendix D to demonstrate the exogeneity of absenteeism in this context.

4.2 Results

Table 2 presents the results from the estimation of equation (1), and the results confirm each of the model's predictions, in turn. First, the results confirm that number of workers borrowed increases when i's state deteriorates compared to j's. Specifically, we find that when the average difference in the states increases by 1% (5%), the number of workers borrowed by manager i from manager j increases by 5-6% (28-34%).[46] To illustrate the size of the effect, consider a case where a manager has 1% absenteeism and borrows 1 worker from each of their 3 main partners who have no absenteeism. In other words, the main coefficient is 0.005 for all 3 main partners. The manager would borrow 1 more worker across the 3 partners, or 4 workers in total that day, if their absenteeism were to increase to 10.8-12.6%. If the managers absenteeism were to rise to 24.8-29.2%, they would borrow 1 additional worker from each of their main partners, for a total of 6 workers borrowed that day.

We find that a manager in a relationship that is more mature by 10 days compared to the average relationship, borrows approximately 34% more workers from that partner.[47] Hence, a manager that borrows 1 worker in an average partnership would borrow 1 more worker every 3 days in a partnership more mature by 10 days or 1 more worker every day from a partnership more mature by 28 days.[48] All else equal, a manager borrows approximately 29% less from a manager that is 12

[46]The first coefficient is in decimals. The equation for the number of workers borrowed is $\theta_{ij}^1 = e^{\beta_1 x_1 + X\beta}$. Consider a case where the main coefficient, x_1, increases by 1% (0.01), then $\theta_{ij}^2 = e^{\beta_1 x_1 + \beta_1 0.01 + X\beta}$. Therefore, $\theta_{ij}^2 - \theta_{ij}^1 = (e^{\beta_1 0.01} - 1)\theta_{ij}^1$ and the percentage change in the number of workers borrowed is given by $100 \times \frac{\theta_{ij}^2 - \theta_{ij}^1}{\theta_{ij}^1} = 100 \times (e^{\beta_1 0.01} - 1)$. Using the coefficient in column 1, we find that when x_1 increases by 1%, the number of workers borrowed increases by $100 \times (e^{5.81 \times 0.01} - 1)$ = 5.98%. From column 3, we find that borrowing increases by $100 \times (e^{5.91 \times 0.01} - 1)$ = 5.03%.

[47]The average maturity of partnerships is 40.06 days. 10 days represent a 24.96% increase from average. We find that this increase translate into a $100 \times (e^{1.308 \times ln(1.2496)} - 1)$ = 33.83% increase in borrowing in column 2 and $100 \times (e^{1.3117 \times ln(1.2496)} - 1)$ = 33.95% in column 3.

[48]It is important to note that the measure of maturity is only a proxy for longer relationships since the average manager has been managing their given line for about two years (mean 1.92, SD 1.90 years), but we only observe a subset of these relationship histories. The results still indicate that maturity is associated with trade intensity, but the

feet away compared to a manager 3 feet away.[49] Or, a manager who borrows one worker from a line 15 feet away would borrow one additional worker each day from a line only 3 feet away.

Next, we investigate whether the behavior of managers is also affected by their demographic differences. We find that managers borrow 61-63% less from partners of different gender than with managers of the same gender.[50] This means that a manager borrowing 1 worker from a partner of a different gender would borrow 1.6-1.7 additional workers daily from a partner of the same gender. Additionally, when looking at the coefficients in column 2 and 3, we find that a manager borrows approximately 16% less from managers with a different level of education. A manager borrowing 1 worker from a partner with a different level of education would borrow 1 additional worker from a partner with the same level of education every 5 days.

Finally, we find that differences in age and experience also affect the trade behavior of the managers. Indeed, a manager tends to borrow 6.5-11% less from managers 10 years different in age than with managers within a difference of 1 year of age.[51] That is, a manager borrowing 1 worker from a partner younger or older by 7 years would borrow 1 additional worker from a partner 1 year their junior or senior every 10 days. Similarly, managers tend to borrow more from partners with similar levels of experience managing their current line. They tend to borrow 23-33% less from managers with 5-years difference in experience than from managers with just 1 year difference in experience. That is, a manager borrowing 1 worker from a partner with a 5-year difference in experience would borrow 1 additional worker every other day from a partner with the same level of experience.[52]

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magnitude is to be taken with care. In Figure 7, we investigate trading activities from a given incumbent manager when a new manager replaces an existing main partner. We find that it takes about 4 months for these new partnerships to go back to the level of trade of older partnerships. Including a dummy for whether either manager in a given dyad has been on the line for 4 months or less, only slightly changes the coefficients, but the magnitudes and significance level don't change meaningfully, which is true for the maturity coefficient as well. This indicates that while the measure of maturity sometimes proxies for potentially longer relationships, these longer relationships do not seem to drive the magnitude of the coefficient.

[49] The percentage change is $100 \times \frac{(e^{-0.246 \times ln(12)} - e^{-0.246 \times ln(3)})}{e^{-0.246 \times ln(3)}}$ = -28.93% in column 2 and -28.89% in column 3.

[50] When the dummy variable goes from 0 to 1, the effect is $100 \times (e^{\beta} - 1)$ percent.

[51] The percentage change is $100 \times (e^{-0.029 \times ln(10)} - 1)$ = -6.46% in column 1, and 10.9% in column 2 and 3.

[52] Recall that in subsection 2.6, we showed that the location of the managers in the factory is unrelated to how similar they are to managers around them. We also showed that physical distance and the demographic distance variables are highly uncorrelated between one another which could have limited our ability to interpret the coefficients of the regression.

Table 2: Empirical tests of relational contracts

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	5.8103	5.2897	4.9104
	(2.0057)∗∗∗	(1.7518)∗∗∗	(1.6650)∗∗∗
	[2.0167]∗∗∗	[1.7663]∗∗∗	[1.6870]∗∗∗
	{2.5503}∗∗	{2.0001}∗∗∗	{1.9338}∗∗
log(Maturity of relationship)	0.3475	1.3079	1.3117
	(0.1179)∗∗∗	(0.0871)∗∗∗	(0.0866)∗∗∗
	[0.1193]∗∗∗	[0.0880]∗∗∗	[0.0875]∗∗∗
	{0.1344}∗∗∗	{0.0933}∗∗∗	{0.0932}∗∗∗
log(Distance)	−0.8361	−0.2463	−0.2459
	(0.1177)∗∗∗	(0.0842)∗∗∗	(0.0839)∗∗∗
	[0.1191]∗∗∗	[0.0860]∗∗∗	[0.0857]∗∗∗
	{0.1314}∗∗∗	{0.0954}∗∗∗	{0.0949}∗∗∗
	Identity-based distance		
Different gender	−0.9506	−0.9934	−0.9978
	(0.2415)∗∗∗	(0.2087)∗∗∗	(0.2114)∗∗∗
	[0.2357]∗∗∗	[0.2049]∗∗∗	[0.2081]∗∗∗
	{0.3378}∗∗∗	{0.3550}∗∗∗	{0.3580}∗∗∗
Different education	−0.5023	−0.1835	−0.1836
	(0.1282)∗∗∗	(0.0913)∗∗	(0.0911)∗∗
	[0.1299]∗∗∗	[0.0924]∗∗	[0.0923]∗∗
	{0.1243}∗∗∗	{0.0811}∗∗	{0.0808}∗∗
log(Difference in age of managers)	−0.0290	−0.0500	−0.0500
	(0.0185)	(0.0157)∗∗∗	(0.0157)∗∗∗
	[0.0184]	[0.0156]∗∗∗	[0.0156]∗∗∗
	{0.0192}	{0.0161}∗∗∗	{0.0162}∗∗∗
log(Diff. in exp. on the line)	−0.1611	−0.2564	−0.2567
	(0.0969)∗	(0.0785)∗∗∗	(0.0783)∗∗∗
	[0.0958]∗	[0.0770]∗∗∗	[0.0768]∗∗∗
	{0.0789}∗∗	{0.0818}∗∗∗	{0.0816}∗∗∗
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	5.98 %	5.43 %	5.03 %
Effect when X1= 5%	33.71 %	30.28 %	27.83 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different genders, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table 3: Shock history matters

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	6.7109	6.1471	5.7792
	(1.8103)∗∗∗	(1.5942)∗∗∗	(1.5239)∗∗∗
	[1.8287]∗∗∗	[1.6207]∗∗∗	[1.5570]∗∗∗
	{2.4126}∗∗∗	{1.9317}∗∗∗	{1.8820}∗∗∗
Shock history	−2.1143	−1.9920	−2.2049
	(0.8546)∗∗	(0.7056)∗∗∗	(0.6968)∗∗∗
	[0.8868]∗∗	[0.7356]∗∗∗	[0.7274]∗∗∗
	{0.9789}∗∗	{0.7632}∗∗∗	{0.7581}∗∗∗
log(Maturity of relationship)	0.3368	1.3162	1.3198
	(0.1283)∗∗∗	(0.0846)∗∗∗	(0.0845)∗∗∗
	[0.1298]∗∗∗	[0.0856]∗∗∗	[0.0856]∗∗∗
	{0.1469}∗∗	{0.0948}∗∗∗	{0.0953}∗∗∗
log(Distance)	−0.8417	−0.2418	−0.2418
	(0.1225)∗∗∗	(0.0834)∗∗∗	(0.0833)∗∗∗
	[0.1240]∗∗∗	[0.0854]∗∗∗	[0.0852]∗∗∗
	{0.1363}∗∗∗	{0.0946}∗∗	{0.0941}∗∗
	Identity-based distance		
Different gender	−0.9426	−0.9977	−1.0016
	(0.2424)∗∗∗	(0.2096)∗∗∗	(0.2132)∗∗∗
	[0.2362]∗∗∗	[0.2050]∗∗∗	[0.2091]∗∗∗
	{0.3439}∗∗∗	{0.3604}∗∗∗	{0.3636}∗∗∗
Different education	−0.4992	−0.1735	−0.1745
	(0.1305)∗∗∗	(0.0919)∗	(0.0918)∗
	[0.1323]∗∗∗	[0.0928]∗	[0.0928]∗
	{0.1261}∗∗∗	{0.0808}∗∗	{0.0806}∗∗
log(Difference in age of managers)	−0.0295	−0.0512	−0.0513
	(0.0186)	(0.0158)∗∗∗	(0.0159)∗∗∗
	[0.0185]	[0.0158]∗∗∗	[0.0158]∗∗∗
	{0.0192}	{0.0161}∗∗∗	{0.0163}∗∗∗
log(Diff. in exp. on the line)	−0.1614	−0.2575	−0.2570
	(0.0979)∗	(0.0790)∗∗∗	(0.0788)∗∗∗
	[0.0968]∗	[0.0775]∗∗∗	[0.0772]∗∗∗
	{0.0786}∗∗	{0.0809}∗∗∗	{0.0805}∗∗∗
Observations	27498	27498	27498
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	6.94 %	6.34 %	5.95 %
Effect when X1= 5%	39.87 %	35.98 %	33.5 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the average difference in absenteeism in the pair over the last 7 days, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

On the whole, these results show that managers do indeed borrow more from their partners as they are hit by stronger absenteeism shocks than their partners. The positive coefficient of the maturity of the relationship indicates that trust evolves with the number of interactions between the managers. Additionally, the results suggest that both physical and identity-based, or demographic, distances impose substantial barriers on relationship formation and dynamics.

The longstanding literature on risk sharing predicts that the incentive compatibility constraint can be relaxed if agents consider the recent history of shocks (see, e.g., Udry (1994) and Ray (1998)). For example, suppose that a manager had low absenteeism relative to their partner for, say, a week prior, putting them in a better lending position for that week, and get hit by a high absenteeism shock today. The partner may be willing to lend more workers to the manager that day than they otherwise would if the shock history was ignored by the managers. In Table 3, we add the average absenteeism difference between the managers in the pair over the last 7 days, excluding the day of the observation. This regressor is positive when the observed manager had relatively more absenteeism than their partner over the last week. Our results are in line with the prediction of the literature: the larger (smaller) was a manager's absenteeism compared to that of their partner, the less (more) they can borrow from that partner today. In particular, a manager would be able to borrow approximately 10% more on a given day if their absenteeism over the last 7 days was 5% smaller than their partner's on average, compared to a case where both had the same level of absenteeism over the previous week. This result provides further evidence of the relational nature of the exchanges between managers.

In terms of robustness, we show in Appendix G that our main results presented in Table 2 are virtually identical when controlling for whether the two lines in a pair are working on the same style of garment. This evidence helps to alleviate concerns that trading between lines closer to each other on the factory floor and/or otherwise more likely to trade intensively does not simply reflect the probability of working on the same order, which anyway happens rarely. Finally, in Appendix H, we look at whether trade patterns differ with respect to high and low-efficiency workers. As is predicted by a generalized version of the model in which workers are of differing quality, we find that managers are more selective of the partners with whom they trade their higher-productivity workers.[53]

Table G1 reports the result of a logistic regression and shows how the main variables affect the odds ratio of borrowing. The direction of the effects we found for the intensive margin are preserved here along the extensive margin. From columns 2 and 3, we find that when the average difference in absenteeism is 5%, the odds of manager i borrowing from manager j increase by 27%

[53] From our discussion with the firm, we know that workers have no say in where they are assigned on a given day. Consistent with this, we find that traded workers are not more likely to be assigned to lines where more workers speak their language and therefore, more likely to be in their friend network (not shown). Their earnings and separation probability also are not affected by whether they are traded, suggesting that their job satisfaction does not suffer from this. Consistent with the latter, line-level absenteeism on a given day is unaffected by the number of workers this line traded in the previous days. Hence, we believe that the paper captures the key elements of trading dynamics.

compared to a scenario where both managers have the same level of absenteeism. We find that the odds of borrowing are 182% larger in a partnership twice as mature. The odds that i borrows from j decrease by 34.5% if j is 6 feet away from i rather than 1 foot away. The odds of borrowing between managers of a different gender or of a different level of education are 52.75% and 26.5% lower, respectively, compared to borrowing between similar managers. Finally, doubling the age difference and the experience difference of the managers reduces the odds of borrowing by 3% and 14.8%, respectively.

4.3 Central reorganization of workers across lines to avoid delays

As mentioned above, Adhvaryu et al. (2021) show that upper management sometimes preemptively reassigns high-efficiency workers to low-productivity lines at the beginning of an order, particularly from important buyers, to lower the chance of missing the order delivery deadline. This leads to a Negative Assortative Matching (NAM) between workers and managers at the beginning of the order. In these cases, workers are reassigned for a relatively long period of time. In Appendix A, we show that excluding trades that occur in the first week of an order or longer trades, which are more likely to be centrally planned, has little effect on the results.

First, as mentioned before, the distribution of borrowing spells matches closely the distribution of absenteeism spells of workers (see Figure 1). 40% of absenteeism spells last 1 day, with 65% of them lasting 3 days or less. Similarly, 50% of borrowing spells last for a day and 70% last for 3 days or less. In the left panel of Figure 2, we show that the average borrowing spell length is around 6 days for trades initiated during the first week of an order; while it falls to 2.5 days for trades initiated after the first week.[54] The right panel shows that about 30% of workers borrowed during the first week of a borrower's order are borrowed for one week or more; while this percentage falls to 8% in subsequent weeks consistent with the evidence shown in Adhvaryu et al. (2021). Moreover, 75% of workers borrowed after the first week of an order are borrowed for 1-2 days; while this is the case for only 40% of trades during the first week.

Next, we count the number of high- and low-efficiency workers traded from high-efficiency lines to other high-efficiency lines, from low-efficiency to low-efficiency lines, and between high- and low-efficiency lines. When excluding long trades and those initiated in the first week of an order to ignore worker moves most likely to reflect upper management's preemptive reorganization of workers across lines, Figure 3 shows that workers are much more likely to flow between lines of similar efficiency levels than they are to flow between lines of differing average efficiency and that flows of high- and low-efficiency workers are balanced. If these remaining worker moves were still reflecting the NAM pattern identified in Adhvaryu et al. (2021), we would expect most trades to

[54]The average order is 17-18 work days long with the median order lasting more than 14 work days.

involve high-efficiency workers and to occur between lines of differing efficiency.

In Figure 4, we reinforce this idea by showing that managers are much more likely to form main partnerships with managers of similar efficiency levels. That is, high-efficiency (low-efficiency) managers are more likely to establish their main partnerships with other high-efficiency (low-efficiency) managers on their floor than they are to form partnerships with managers of differing efficiency. Finally, having established that excluding long trades or those initiated in the first week of an order isolates trades least likely to reflect the preemptive reorganization of production by upper management to avoid missed deadlines for important buyers, we check that our main results are robust to excluding these worker moves. Tables A1 and A2 show that the results presented in Table 2 are statistically and qualitatively similar when excluding long spells and moves initiated in the first week of an order, respectively.

Note we do not mean to imply that upper management has no interest or involvement in the absenteeism-induced short-term sharing of workers by way of these relationships. It is, of course, possible or even likely that upper management encourages managers to help each other with their absenteeism-related worker needs, and that the desire to appear cooperative to upper management might enter the incentive compatibility constraint in some way. The results just indicate that the span of control and/or informational asymmetry problems we mention above are large enough to make central coordination of the redistribution of workers impossible, leaving need for relational contracts to determine cooperation.

4.4 Determinants of trading activity

We next investigate if key dimensions of managerial quality shown to be predictive of high-productivity lines in Adhvaryu et al. (2023b) are correlated with trading intensity. Note that we include line fixed effects in the main regression specifications above such that managerial quality does not drive the pairwise trading patterns shown. However, in addition to the transaction costs modeled and investigated above, managerial traits or practices might determine a particular manager's need for or reliance on trading.

Table 4 shows that managers exhibiting greater Control (i.e., a stronger belief in their own ability to impact performance rather than acquiescing to fate or chance) are more active traders. This pattern is consistent with the results in Adhvaryu et al. (2023b) showing Control to be one of the strongest contributors to line productivity. On the other hand, we also see that managers exhibiting greater Attention are less active traders, and to a much smaller extent those with more Autonomy. Autonomy captures the managers' proactiveness in identifying and solving production problems on their own. Attention captures the managers' general effort to ensure a smooth production. In particular, it captures their effort to meet production targets and the frequency at which they monitor the production.[55] This pattern is consistent with a stronger ability to leverage within line worker-task reassignments to mitigate any potential productivity losses as demonstrated in Adhvaryu et al. (2022a). That is, if a manager is more able to make do with the workers they have, their need to borrow (and therefore interest in maintaining partnerships through lending) would be subdued.[56]

Table 4: Determinants of trading activity

	(1)
	Number of workers borrowed
Autonomy	-0.0777*
	(0.0444)
Control	0.268***
	(0.0445)
Attention	-0.188***
	(0.0587)
log(Days since order started)	0.0441
	(0.0462)
Observations	9494
Mean of Y	48.26
SD	16.30

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the total daily number of workers borrowed by managers on managerial characteristics and on the log of the number of days since the order started. We include standardized measures of Autonomy, Control, and Attention. Autonomy captures the degree to which managers take the lead in and responsibility for solving and identifying production problems. Locus of Control captures the managers' belief in their own ability to impact performance rather than acquiescing to fate or chance. Attention captures the managers' general effort to ensure a smooth production, including the frequency with which they monitor. We control for demographics of managers such as gender, language, birth location, education, caste, experience, and age. We also include unit, year, month, day of the week, and style fixed effects. We cluster the standard errors reported in parentheses at unit by date level.

We also include the same learning-by-doing measure used in Adhvaryu et al. (2023b) to check whether an imbalance in length of orders across managers might be driving any observed patterns in trading activity. The small and insignificant coefficient helps to alleviate concerns that learning-by-doing is confounding any of the results. As mentioned above, we also control for this measure in our main specifications.[57]

5 Simulations

Before concluding, we report the results of several counterfactual simulations to study the extent to which firm investments in relationship formation would help solve the worker misallocation

[55] See Adhvaryu et al. (2023b) Section 2.3 for a detailed explanation of the variables.

[56] Adhvaryu et al. (2023b) identify seven factors of managerial quality, but we focus here on those which proved most important for productivity in that analysis. We exclude only Tenure as it is likely correlated with both ability to make do with available workers and age of relationships but would be less clearly interpretable than the pair-wise measure we already use above.

[57] We can include separately absolute differences in Attention, Autonomy, and Control in the main regression (Table 2), which has no meaningful impact on the other coefficients. Controlling for individual levels of Attention, Autonomy, and Control by way of manager fixed effects (the specification in column(3) of Table 2), we find that differences in Autonomy between partners reduces trades, but only at the 10% significance level. In particular, a 1SD difference reduces trade by 10.7%. The exact channel is hard to pin down like with the other demographics, but one could imagine that manager *A* who is more careful in minimizing problems on their own line may not be inclined to trade as many workers to manager *B* if *A* believes that *B* would not need as many workers if manager *B* was more careful as well, all else equal.

problem resulting from idiosyncratic absenteeism realizations across lines. The global garment industry is highly competitive and characterized by low profit margins. From previous work and discussions with the firm we estimate that approximately 5% of the revenues are converted into profits. Further, each percentage point increase in efficiency translates into a 0.1875-0.25 percentage point increase in profit, all else equal (Adhvaryu et al., 2023a). This implies that a one percentage point increase in efficiency represents a 3.75-5% increase in the *profit margin*. We use this information to get a rough estimate of how the counterfactuals could affect profits for the firm. It is important to emphasize that here we assume that the profit margin itself is not affected by the counterfactuals, which, of course, is a simplification of reality, but may provide useful information for the firm.[58]

For the simulations that follow, we begin by estimating a reduced-form production function. For this, we first reproduce Figure 5, panel (b), which measures the link between the number of workers actually working on a line as a percentage of the line size, but partial out line, year, month and day-of-the-week fixed effects, and fit a monotonic five-degree polynomial between (residualized) efficiency and (residualized) percentage of workers on the line. The polynomial is then used as our estimated reduced-form production function and is presented in Figure I1.[59]

The gist of our simulations is as follows. For any given day, we observe the *status quo* equilibrium distribution of worker absenteeism shock realizations as well as lending/borrowing behavior on the part of managers. We then amplify (or restrict) this behavior by increasing (decreasing) the flow of workers across new relationship pairs, further decreasing (increasing) the misallocation of workers across lines. We then use the "production function" estimated above to determine the resulting line productivity and aggregate (plant-day-level) productivity effects following a change in the number of workers working on a line induced by the simulation.[60] We iterate this procedure for a given number of days to estimate the mean and standard error of the impact estimate. We present the comparisons of the resulting productivities across all simulations in Figure 8 below. There are two types of simulations. In the first group, we simulate what the trades of managers exploiting their relational contracts would look like under various scenarios. To remain conservative in our estimates, we assume that the observed number of workers on a line

[58]For example, if absenteeism falls, lines may meet their target more often and get a small bonus and in turn, ensure that the garment order is completed faster, both of which could affect the profit margin.

[59]As shown in the results section, learning-by-doing has little impact on trading patterns. Consequently, partialling out the log of the number of days since the beginning of an order has virtually no impact on the production function. As we further mention below, to produce conservative estimates and to remain consistent with the previous section of the paper, we assume that workers received by a line during the first week of an order are done centrally. We exclude these observations when computing the reduced-form production function.

[60]In all simulations, we assume the production function that is implied by Figure I1. That is, we assume that the relationship between the percentage of workers on the line and efficiency is approximated by the fifth degree polynomial displayed in FIG. We also assume throughout that the production function remains fixed before and after the counterfactual policy change.

during the first week of an order is fully determined centrally and that the number of workers for that line that week would not change if, say, the manager of that line had relational contracts with three additional managers. That is, we assume that lines in the first week of an order would not engage in additional trades, imposing a lower bound on the relational contract simulations. In the second group of simulations, we aim to simulate what a central planner could achieve. For these simulations, we put no restrictions on how a planner would redistribute workers based on whether a line is in the first week of an order.

5.1 Benchmarks

We study several benchmark scenarios – no redistribution of workers (maximal misallocation); perfect redistribution (no misallocation); and an exogenous reduction in absenteeism.

No redistribution. We begin by asking what the simulated productivity losses are, going from the *status quo* level of redistribution via relationships to a counterfactual scenario in which relational contracts are shut down – i.e., there are no worker transfers across lines. This simulation is equivalent to increasing transaction costs to a point where any trade is too costly. In this scenario, managers must make do with only present home-line workers; that is, absenteeism shocks are not smoothed at all, and worker misallocation is maximized.

We start by drawing 100 production days (without replacement) at random. For each day, we compute the predicted efficiency with the current trades by plugging the percentage of workers on the line into the estimated production function. To compute the scenario without trade, we use only the percentage of home-line workers present in our estimate. The number of home-line workers in the unit would be the number of workers on the line if lines did not trade. We repeat this exercise 100 times and compute the mean and standard error across the replications. All changes reported in the simulation section are statistically different at the one percent level. We find that efficiency falls when trade is shut down entirely by 0.24 percent (SE 0.004), which corresponds to a decrease of 0.46-0.62% in the firm's profit margin (a decrease of $231,000-$308,000 per year in profit).

Optimal redistribution. As a second benchmark, we study productivity under a counterfactual scenario with perfect redistribution of available workers across lines. This represents the first-best (*ex post*) solution for the firm, conditional on the pattern of worker absenteeism realizations observed in the data.[61] This scenario represents the maximum efficiency that could theoretically be achieved and represents, therefore, an upper-bound. Comparing other efficiency-enhancing scenarios to this first-best case, as a result, yields conservative estimates. In the optimal redistribution simulation,

[61] This scenario represents the maximum efficiency that the firm could theoretically have achieved *ex post* if there were no frictions. In this scenario, the central planner can observe absenteeism and workers' *ex post* productivity without error. The production function of each line before and after redistribution is known and there is no transaction cost.

we compute the loss (gain) of every line in the unit from losing (gaining) 1 worker. The central planner takes a worker from the line with the smallest loss then gives that worker to the line with the largest gain. The exercise is repeated as long as the smallest loss is less than the largest gain.[62] We draw 100 days and perform this procedure on each day; we then repeat this exercise 100 times to compute standard errors around simulated treatment estimates. Efficiency is expected to increase by 1.28 percent (SE 0.015), which translates to a 2.49-3.32% increase in the profit margin (1.24-1.66 million dollars increase).[63]

Reducing absenteeism by half while shutting down trade. Then, we study a benchmark scenario in which the firm (say, via high-powered incentives) reduces absenteeism on each line by half. Within this scenario, we study the same two sub-cases as above. Let us first consider a case where lines do not trade at all and keep their additional home-line workers that are present due to the decrease in absenteeism. We find that the average efficiency increases by 2.11 percent (SE 0.006), a 4.1-5.46% increase on the profit margin (2.05-2.73 million dollars).

Reducing absenteeism by half plus optimal redistribution. We also consider a case where all workers including the additional workers that are present due to the reduction in absenteeism are optimally just like in the optimal redistribution case. We find that the average efficiency increases by 2.88% (SE 0.01) translating to a 5.57-7.43% increase in the profit margin (2.78-3.72 million dollars).

5.2 Policy counterfactuals

One strategy that the firm could do is to hire a buffer stock of floating workers on every floor that could be distributed optimally daily to lines on that floor. In the next two simulations, we explore this idea. We assume that every factory floor has a buffer stock of workers equal to 2% of the number of workers employed on the floor, corresponding to approximately 20 workers. The buffer stock of workers on any given day is subject to the average daily percentage of absenteeism of the unit. The floating workers present that day are first traded optimally within their assigned floor and remaining floating workers are then traded optimally across floors to ensure that no floating workers remain idle. Just like before, we iterate this procedure 100 times.

[62] We repeat that exercise for increments of 0.1, 0.01, and 0.001 workers to reflect the fact that workers can potentially be traded for a fraction of a day and fully exploit the gains from trade. Note that throughout the previous sections, we used data points from lines from which we had reliable productivity information. For the redistribution simulations, we first keep days for which all those lines have recorded productivity and fill in the lines for which we lack information. We assume that these later lines are of the average size and have the average absenteeism of the reliable-data lines in that unit that day. This ensures that workers can be traded to and borrowed from these lines in the simulations.

[63] Perhaps there exist logistical constraints that would limit even a central planner's ability to transfer workers costlessly across floors. Limiting optimal trades to take place within floors would yield a smaller increase in efficiency of 1.05% (SE 0.004); a 2.03-2.72% increase in the profit margin or a 1.01-1.36 million $ increase per year in profit. The true achievable maximum is likely to situate itself between these two scenarios.

Floating workers and no trades from managers. We first investigate how efficiency would change if managers used only their own available workers and the floating workers. I.e., if the managers did not trade between one another and the only coping mechanism was the floating workers. We find that in this case, efficiency would increase by 0.86 percent (SE 0.004).

Floating workers distributed post trades from managers. We also consider a case where managers first trade workers as they did in the data. Then, the buffer workers are distributes as presented above, but where managers cannot then trade the buffer workers. In this case, efficiency would increase on average by 1.19% (SE 0.002). It is, of course, hard to interpret how these two simulations would translate into profit as a large number of new workers would need to be hired. The simulations nevertheless show that they could achieve similar gains in efficiency than the optimal trade of existing workers presented above.

In the next two simulations, we investigate the role of physical and identity based distance. We postulated throughout the paper that these distances can affect the transaction cost within pairs of managers in various ways. While it may not be possible to eliminate these differences, asking what would be the effect of removing them can inform us on the importance of these barriers to trade.

Reducing physical distance plus optimal redistribution. We first investigate how reducing physical distance would affect efficiency. In particular, we ask what would be the effect of reducing the average physical distance to 1 foot assuming that trades are done optimally. From column 3 of Table 2, we find that lines would borrow on average 73.36% more if the distance would fall to 1 foot on average.[64] To compute the effect of decreasing physical distance, we proceed in a similar way as we did previously.

For every day that we draw, we compute the average number of workers borrowed in every unit. Then, we calculate what would be this average if it were to increase by 73.36%. We trade workers optimally until this new average is reached or until there are no gains from trade as we did for the optimal trade policy change in the optimal distribution case. We repeat the exercise 100 times to compute the standard errors. We find that reducing distance would increase efficiency by 0.57% on average (SE 0.004) – a 1.10-1.47% increase in the profit margin ($552,000-$736,000). While it may not be possible to physically reduce distance, it may be possible for the firm to design tools tracking the number of home-line workers present, the number of broken machines, the order and the deadline of that order for each line and make the information accessible to all managers such that they can more readily monitor lines further away from theirs.[65]

[64]All else equal, the predicted number of workers borrowed in pairs 9.37 feet away (the average), is given by $\theta_{ij}^{\bar{D}} = e^{X\beta - 0.2459\times ln(9.37)} = e^{X\beta}e^{-0.2459\times ln(9.37)}$. If distance were equal to 1, the predicted number of workers borrowed would be $\theta_{ij}^{1} = e^{X\beta - 0.2459\times ln(1)} = e^{X\beta}$, where $X\beta$ represent the other variables in the regression. Therefore, all else equal, we would expect the number of workers borrowed to increase by $\frac{e^{X\beta} - e^{X\beta}e^{-0.2459\times ln(9.37)}}{e^{X\beta}e^{-0.2459\times ln(9.37)}} = \frac{1-e^{-0.2459\times ln(9.37)}}{e^{-0.2459\times ln(9.37)}}$ =0.7336 or 73.36% on average.

[65]As we explained in Subsection 2.5, the current data recording system does not provide real-time data, which, along

Reducing demographic distance plus optimal redistribution. Next, we investigate whether there are gains from reducing demographic distances among the managers. The aim is to reduce gender, education, age and experience differences simultaneously. If we were to use the estimates in Table 2, we would ignore the fact that some demographic characteristics may be correlated with one another. To circumvent this problem, we construct a binary variable equal to 1 whenever the managers in a pair have any demographic differences.[66] Then, we estimate the same regression as before except that we use this single binary variable as a measure of demographic difference. The results are presented in Appendix I. Using the estimates in column 3, we find that the number of workers borrowed in dissimilar pairs would increase by 37.64% if demographic differences were eliminated.[67] In our sample, 92.5% of pairs have any demographic differences. Hence, if demographic differences were to be eliminated, we would expect that the average number of workers borrowed would increase by 37.64% for 92.5% of pairs. In other words, we would expect that the daily number of workers borrowed would increase by 37.64%×92.5%=34.82% on average.

To compute the effect of decreasing demographic differences, we proceed in a similar way as before. For every day that we draw, we compute the average number of workers borrowed in every unit. Then, we calculate what would be this average if it were to increase by 34.82%. We trade workers optimally until this new average is reached or until there are no gains from trade. We repeat the exercise 100 times to compute the standard errors. We find that the average efficiency increases by 0.42% (SE 0.003), corresponding to a 0.82-1.10% increase in the profit margin ($413,000-$550,000). While it is not desirable to eliminate demographic differences, the firm could limit the barriers they impose on trade by favoring integration and social activities between managers, potentially allowing them to see past those initial difference and establish relational contracts with a larger number of colleagues.

Figure 8 plots the percentage change from baseline under all simulations on the left y-axis and the profit change in millions of USD on the second vertical axis.[68] Comparing the no-trade scenario to the optimal trade scenario under the observed level of efficiency reveals that trades are left on the table and that the firm would benefit from amplifying trading between the managers. In fact, the current level of trade exploits about 15% of the potential efficiency gains with the current number

with other logistical issues, would be ill-suited as it is to design such tool. However, it may be possible to improve the data-recording system along these lines.

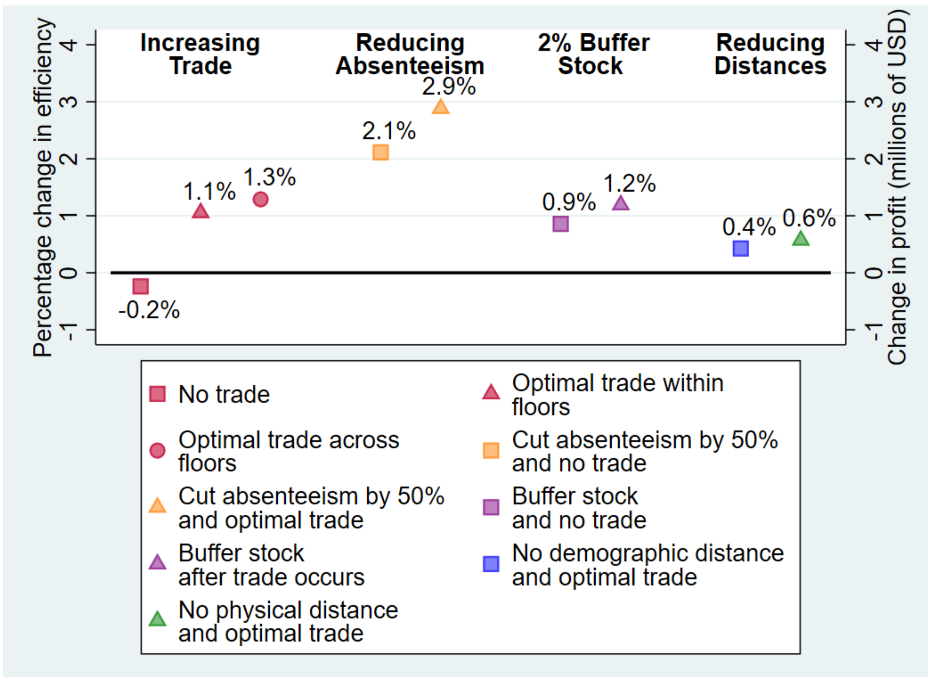
[66] More precisely, this variable equals 1 when managers are of different genders, or have a different level of education, or their age difference is above median, or their experience difference is above median.

[67] All else equal, in demographically dissimilar pairs, the predicted borrowing is $\theta_{ij}^{1} = e^{X\beta - 0.3195\times 1} = e^{X\beta}e^{-0.3195}$ and in similar pairs, $\theta_{ij}^{0} = e^{X\beta - 0.3195\times 0} = e^{X\beta}$, where $X\beta$ represent the other variables in the regression. Therefore if dissimilar pairs were to become similar, we would expect trade to increase on average by $\frac{e^{X\beta} - e^{X\beta}e^{-0.3195}}{e^{X\beta}e^{-0.3195}} = \frac{1-e^{-0.3195}}{e^{-0.3195}}$ =0.3764 or 37.64%.

[68] All differences between the point estimates are significant at the 1% level. The 99% confidence bands are smaller than the marker size and are not displayed on the graph.

of workers and level of absenteeism.[69] Increasing trades by way of either reducing demographic or physical distances or by reducing their negative effects on partnership formation, could potentially allow the firm to exploit 0.44-0.53% of the potential efficiency gains via low-cost interventions as pointed out above. The simulations suggest that to reach larger gains in efficiency, the firm may need to engage in more costly interventions such has hiring floating workers or devising ways to reduce absenteeism.

Figure 8: Plant-level gains in efficiency across simulations



Note: As a baseline, we first compute predicted efficiency given by the data. We then compute the efficiency gain from this baseline when absenteeism remains at its observed level, but managers do not trade (first marker) and when workers are traded optimally within floor (second marker), and across floors (third marker). Then, we compute the efficiency gain when absenteeism falls by half for every line and managers do not trade (fourth marker), and when workers are traded optimally (fifth marker). Next, we investigate what would happen if each floor had a 2% buffer stock of workers traded optimally within floors if managers didn't trade their home-line workers (sixth marker) or if the buffer workers were sent to lines after the lines had traded between one another (seventh marker). Finally we compute the gain in efficiency when workers are traded optimally and demographic distances are eliminated (eighth marker), and when the average physical distance falls to 1 feet (ninth marker).

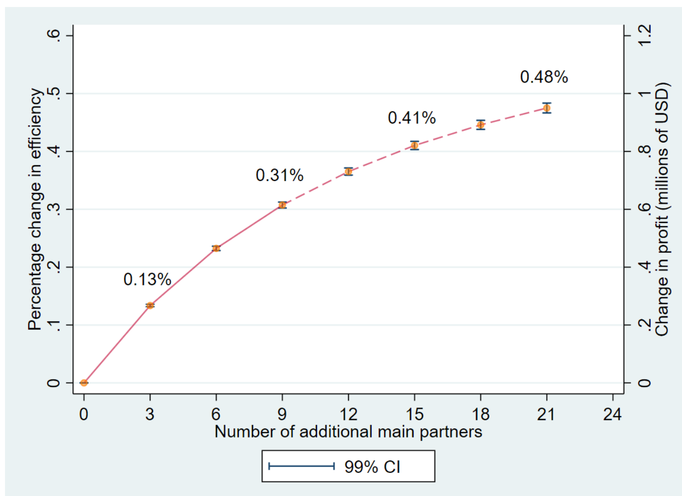
Increasing the number of main partners. We investigate next how valuable are bilateral relationships for the firm. We reproduce our main regression presented in Table 2 and include a dummy variable for whether the partner is one of the manager's 3 main partners. The results are presented in Table I2 of Appendix I. Using the estimates in column 3, we find that a manager borrows 51% more from their main partners than from other partners. In this exercise, we ask what are the gains to increasing the number of main partners. To do so, we proceed in a similar fashion as we did for the demographic distance simulation. We first increase the number of main partners by 3 for every manager. Hence, in a unit with N lines, a manager would see an increase of its number of workers

[69] Or 18.5% if consider only optimal trades within floors.

borrowed by 51% for $100 \times 3/N$ percent of its partners or an increase of $100 \times .51 \times (3/N)$ percent. Since we do the same exercise for all lines in the unit, we would expect the average number of workers borrowed in the factory to increase by that same percentage.

For every day that we draw, we compute the average number of workers borrowed in every unit. Then, we find what would be this average if it were to increase to its new predicted level with 3 additional main partners for every manager. We trade workers optimally until this new average is reached or until there are no gains from trade. We repeat the exercise 100 times to compute the standard errors. We estimate the new efficiency if we add 3 to 21 additional main partners in increments of 3 and present the results in Figure 9.

Figure 9: Plant-level gains in efficiency with additional main partners



Note: As a baseline, we first compute predicted efficiency given by the data, with no additional main partners. We then compute the efficiency when we add 3, 6, 9, 12, 15, 18, and 21 additional main partners. We display the percentage increase in efficiency from baseline above the markers. Note that at baseline, every manager have 3 main partners so only N-3 additional main partners can be added, where N is the number of lines in the unit. The smallest unit has 14 lines. Hence, only 11 additional main partners can be added in that unit. On the dashed segment, we add the minimum between x and N-3 main partners, where x is the value on the x-axis. Hence, on this segment, all partners are main partners in at least one unit. At 21 additional main partners, all partners are main partners in all units.

We find that 3 additional main partners increase efficiency by 0.13% (SE 0.0008) and that when all partners are main partners (21 additional main partners on average across all units), efficiency increases by 0.48% (SE 0.003), respectively. These results suggest that if the firm were able to increase partnerships to a maximum across whole factories, it could achieve about 50% of the efficiency gains possible under the first-best scenario where there are no constraints and all workers are traded optimally, respectively. (This is an upper bound since the cost of maintaining relationships may not increase linearly in the number of partners.) While it might be challenging to design a system where workers are optimally traded without friction, it may be easier for the firm to encourage partnerships and increase the number of main partners. Currently, the firm does not organize mixers, retreats, or similar events for line managers, rather only for higher-level staff and executives. One can imagine that these events could help managers form friendships that may carry to the production floor and help in reducing the initial barriers coming from demographic differences as explained above. The firm could also offer training to promote the notion and value of reciprocity. If the firm were able to increase the number of main partners by just 3 (6) main partners which is virtually equivalent to making all managers main partner within a given floor , we estimate that it could achieve 25% of the potential gains (or 31%) instead of 15% currently achieved and its profit could increase by $172,000 per year (or $300,000). This suggests that overall, relational contracts are highly valuable for the firm.

6 Conclusion

In this study, we document and quantify the importance and the limitations of relational contracts among managers of a large garment manufacturing firm in India. We show that worker absenteeism – particularly large absenteeism shocks – has substantial impacts on team productivity, which is of first-order importance to both managers and the firm. We study how managers leverage relationships to lend and borrow workers in a manner consistent with canonical models of relational contracting. While managers are indeed able to smooth some, mostly small, worker absenteeism shocks, they are unable to leverage relationships to smooth larger shocks, resulting in highly imperfect risk sharing. Managers have strong relationships with about two or three primary partners who are both physically close (on the factory floor) as well as similar in terms of identity characteristics; they transact very sparingly with other managers. This results in many potentially beneficial transfers being left unrealized. This latter suggests that dyad-specific costs of transacting may serve as meaningful barriers to relationship formation and maturity.

Counterfactual simulations allow us to benchmark the value of relationships for the firm. The current level of trade achieves 15-18% of the first-best scenarios where workers are centrally traded which would increase to 20-30% if managers established relational contracts with all of their colleagues on their floor. Our results suggest that the firm may be able to foster relationships at relatively low cost by organizing social events or training on the value of reciprocity that may allow managers to see past initial differences. To allow managers to form, and especially maintain partnerships, across floors may require the firm to develop systems to track worker-level productivity data in real time to allow managers to better monitor each other which is, of course, costly. While we demonstrate that relationships are valuable, the firm would also benefit in terms of productivity gains from developing additional strategies to cope with absenteeism such as hiring floating workers distributed by upper management to lines based on their daily absenteeism. The simulations assume that the counterfactual scenarios only affect trades and no other workplace dynamics. Future research on the topic could leverage carefully designed experiments to establish causally both the value of relationships and the costs and benefits associated with the policies above.

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APPENDIX

A Excluding trades likely to be centrally planned

Table A1: Empirical tests when excluding long trades (6 days or more)

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	6.0416	5.8510	5.7414
	(2.1840) ***	(1.9574) ***	(1.8823) ***
	[2.1636] ***	[1.9159] ***	[1.8456] ***
	{2.6263} **	{2.4984} **	{2.4032} **
log(Maturity of relationship)	0.3176	1.1589	1.1599
	(0.0792) ***	(0.0897) ***	(0.0896) ***
	[0.0815] ***	[0.0890] ***	[0.0889] ***
	{0.0863} ***	{0.0999} ***	{0.0998} ***
log(Distance)	−0.7113	−0.2064	−0.2065
	(0.0951) ***	(0.0780) ***	(0.0779) ***
	[0.0981] ***	[0.0814] **	[0.0813] **
	{0.0957} ***	{0.0904} **	{0.0902} **
	Identity-based distance		
Different gender	−0.5926	−0.6421	−0.6433
	(0.1835) ***	(0.1729) ***	(0.1733) ***
	[0.1687] ***	[0.1560] ***	[0.1565] ***
	{0.3126} *	{0.3105} **	{0.3123} **
Different education	−0.3421	−0.0511	−0.0510
	(0.1092) ***	(0.0727)	(0.0726)
	[0.1129] ***	[0.0753]	[0.0753]
	{0.1165} ***	{0.0929}	{0.0927}
log(Difference in age of managers)	−0.0376	−0.0501	−0.0501
	(0.0193) *	(0.0159) ***	(0.0159) ***
	[0.0187] **	[0.0153] ***	[0.0153] ***
	{0.0230}	{0.0178} ***	{0.0178} ***
log(Diff. in exp. on the line)	−0.0958	−0.1484	−0.1487
	(0.0820)	(0.0588) **	(0.0588) **
	[0.0813]	[0.0579] **	[0.0579] **
	{0.0643}	{0.0575} ***	{0.0574} ***
Observations	27560	27560	27560
Mean of Y	.098	.098	.098
SD	.447	.447	.447
Effect when X1= 1%	6.23 %	6.03 %	5.91 %
Effect when X1= 5%	35.27 %	33.98 %	33.25 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We exclude trades longer than five workdays. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table A2: Empirical tests when excluding the first week of an order

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	7.7340	5.8528	4.7662
	(2.5396)∗∗∗	(1.8141)∗∗∗	(1.7004)∗∗∗
	[2.5140]∗∗∗	[1.8040]∗∗∗	[1.7013]∗∗∗
	{2.9601}∗∗∗	{2.0371}∗∗∗	{2.0016}∗∗
log(Maturity of relationship)	0.3780	1.4202	1.4343
	(0.1282)∗∗∗	(0.0953)∗∗∗	(0.0928)∗∗∗
	[0.1311]∗∗∗	[0.0969]∗∗∗	[0.0946]∗∗∗
	{0.1456}∗∗∗	{0.1077}∗∗∗	{0.1059}∗∗∗
log(Distance)	−0.7595	−0.1275	−0.1254
	(0.1362)∗∗∗	(0.0937)	(0.0916)
	[0.1382]∗∗∗	[0.0946]	[0.0922]
	{0.1540}∗∗∗	{0.1079}	{0.1048}
	Identity-based distance		
Different gender	−1.2557	−1.2863	−1.3414
	(0.2876)∗∗∗	(0.2853)∗∗∗	(0.2813)∗∗∗
	[0.2899]∗∗∗	[0.2974]∗∗∗	[0.2950]∗∗∗
	{0.3198}∗∗∗	{0.3513}∗∗∗	{0.3725}∗∗∗
Different education	−0.4633	−0.1855	−0.2004
	(0.1351)∗∗∗	(0.1054)∗	(0.1033)∗
	[0.1373]∗∗∗	[0.1049]∗	[0.1028]∗
	{0.1145}∗∗∗	{0.1107}∗	{0.1085}∗
log(Difference in age of managers)	−0.0303	−0.0520	−0.0532
	(0.0191)	(0.0226)∗∗	(0.0224)∗∗
	[0.0189]	[0.0221]∗∗	[0.0219]∗∗
	{0.0213}	{0.0248}∗∗	{0.0249}∗∗
log(Diff. in exp. on the line)	−0.1030	−0.2602	−0.2552
	(0.0958)	(0.0944)∗∗∗	(0.0918)∗∗∗
	[0.0951]	[0.0952]∗∗∗	[0.0929]∗∗∗
	{0.0820}	{0.1172}∗∗	{0.1162}∗∗
Observations	14918	14918	14918
Mean of Y	.189	.189	.189
SD	.758	.758	.758
Effect when X1= 1%	8.040000000000001 %	6.03 %	4.88 %
Effect when X1= 5%	47.21 %	34 %	26.91 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We exclude observations from borrowing lines that are in the first workweek of an order. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

B Managerial characteristics and trades

In our counterfactual analysis, we construct a binary variable equal to 1 whenever the managers in a pair have any demographic differences. More precisely, this variable equals 1 when managers are of different genders, or have a different level of education, or their age difference is above median, or their experience difference in managing their current line is above the median. We regress this variable on physical distance and separately on a dummy for whether managers are on a different floor to see if similar managers are clustered together by the firm perhaps to promote cooperation.

Table B1: Relationship between demographic difference and location in the factory

	Demographic distance		
	(1) OLS	(2) Probit	(3) Logit
Physical distance	0.0000	0.0000	0.0000
	(0.0036)	(0.0237)	(0.0500)
Pairs	204	204	204
Diff. floor	0.0280	0.2258	0.4737
	(0.0206)	(0.1526)	(0.3159)
Pairs	864	864	864

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the indicator variable for demographic differences on physical distance for lines on the same floor and on a dummy variable for whether the pair is on a different floor separately. In parentheses, we report robust standard errors.

Table B2: Correlations between physical distance and demographic variables

	Distance	**Gender difference**	**Education difference**	**Age difference**	**Exp. on this line difference**
Distance	1				
Gender difference	0.005	1			
Education difference	-0.081	0.009	1		
Age difference	0.122	0.010	0.073	1	
Exp. on this line difference	-0.063	0.074	-0.035	-0.049	1

Note: We present the correlations between physical distance and the demographic distance variables for the 204 pairs of managers on a same floor.

As is evident, on a given floor, managers that are further away from one another are not more likely to be demographically dissimilar than managers that are close by. Though the point estimates are positive, managers on different floors are not statistically more likely to be dissimilar than managers on a same floor either. This suggests that the placement of managers by the firm does not appear to be related to how similar the managers are. Furthermore, none of these demographic variables are highly correlated between one another or with physical distance as we can see from Table B2.

Table B3: Sample composition of managers

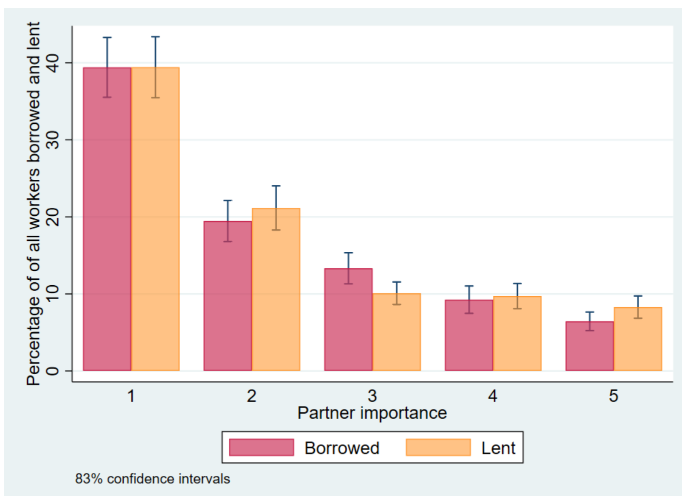
Demographics	**Percent**
Male	87.67
Kannada	75.34
Hindu	97.26
General caste	43.84
Passed 10th grade	41.10
From Karnataka state	71.23

Note: For each demographic variable we show the most common category across managers in the sample. Kannada is the native language and Karnataka state indicates being born in Karnataka but outside of the Bengaluru metropolitan area.

Figure B1: Frequency of trades by workers

Note: We compute the number of times a given worker is traded to another line and plot the distribution. We count only new trades. Hence, if a worker is traded for 2 consecutive days to the same line, we do not count the 2 days as 2 separate trades.

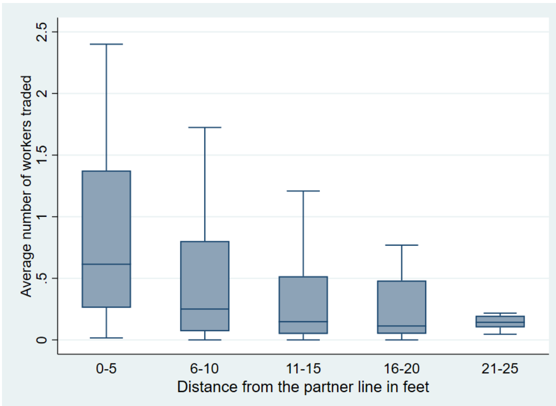
Figure B2: Percentage of all workers borrowed and lent by the importance of partners



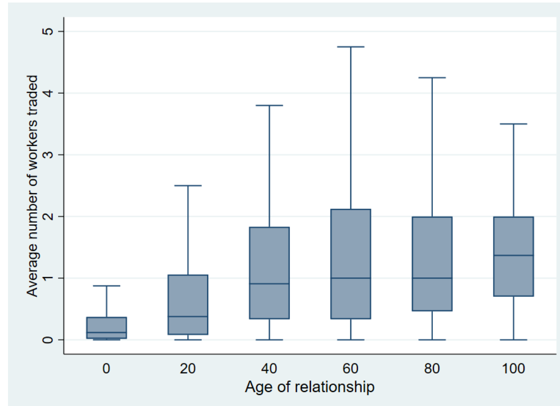
Note: We calculate the frequency of trades between each manager (number of workers traded $\times$ the number of days they are traded). For each manager, we rank its partners by this trade frequency from the most frequent (rank 1) to the least frequent partner. Then, we compute the proportion of all workers borrowed and lent over the span of the data that comes from each of these partners. We plot 83.4% confidence intervals. 83.4% intervals that do not overlap indicate that 2 means are different at the 95% level. At the 95% level and a large number of observations $t = 1.96 \approx (\bar{X}_1 - \bar{X}_2)/\sqrt{se_1^2 + se_2^2}$. With common standard errors $\bar{X}_1 - \bar{X}_2 = 1.96\sqrt{2}se = 1.386se$ which corresponds to an 83.4% confidence interval on the normal distribution. Here, the intervals overlap within partner importance indicating that the exchanges are symmetric and that managers pay back on average the workers they borrow by lending back to their partners.

Figure B3: Average number of workers traded daily

(a) Distance from the partner line



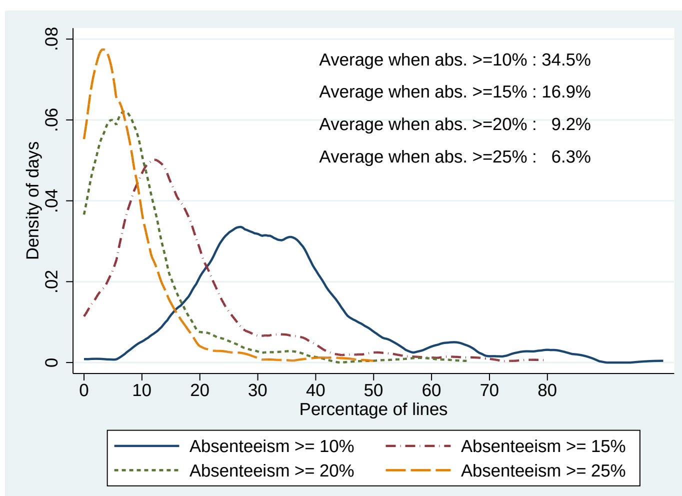
(b) Age of the relationship with the partner line



Note: We compute the number of workers traded (borrowed +lent) daily from a line and each of its partner and plot the distribution by distance bins in feet in panel (a) and in age bins in panel (b). Age is defined by the number of days during which two lines have traded at least one worker with one another. Panel (a) only includes trades done within the same production floor since we do not have measures of distance across floors. We restrict the graphs to trades within 25 feet and within relationships no older than 100 days as few trades are observed beyond these points.

C Absenteeism shocks are uncorrelated and frequent

Figure C1: Frequency of large absenteeism shocks



Note: We calculate the percentage of lines with an absenteeism level of at least 10%, 15%, 20%, and 25% on a given day. We take the average number of lines which such shock across days and plot the distribution. We report the average number of lines with at least a 10%, 15%, 20%, and 25% absenteeism shock. For example, we find that 34.5% (9.2%) of lines have at least a 10% (20%) absenteeism shock on any given day.

Table C1: Intracluster correlation of absenteeism across factories, within factories, and within floors

	Correlation of Absenteeism		
	Within Date	Within Unit and Date	Within floor and Date
Correlation	0.068	0.143	0.145
(SE)	(0.007)	(0.009)	(0.009)

Note: Standard errors are in parenthesis. In column 1, we show the within-day correlation of line-level absenteeism across all lines averaged across days. Column 2 shows the correlation of within-day line-level absenteeism within units averaged across days. Finally, column 3 shows the within-day correlation of line-level absenteeism within factory floors averaged across days.

D Instrumental variable

Some factors may jointly affect absenteeism and efficiency. For example, previous studies from this empirical context have shown that efficiency is impacted by temperature (Adhvaryu et al., 2020) and air pollution (Adhvaryu et al., 2022a). It is also possible that on excessively hot or polluted days more workers decide to stay home. Similarly, a manager may attempt to increase their line's productivity by treating workers harshly or react to poor productivity by scolding workers, driving up absenteeism.

In order to account for such potential endogeneity or reverse causality, we instrument for absenteeism using the number of home-line workers from a state with a major religious festival on a given day. Although most workers are Hindu and many Hindu festivals are common across India, they are often celebrated at different dates in different regions of the country. Moreover, the importance given to different deities is highly heterogeneous across different regions of the country and, as a result, there is much variation in the timing and intensity of festival celebrations. To construct our instrument, we assume that workers are from the state where their native language or dialect is primarily spoken.[70] We compile the dates of all major Hindu festivals across all Indian states. For each line, we define the proportion of their home-line workers that are from a state with a festival at a given date as our instrument.[71]

Managers may anticipate absenteeism for more common festivals like Diwali and plan accordingly. However, workers on any given line come from all over the country. As a result, it is unlikely that managers can anticipate absenteeism stemming from every festival.[72] Indeed, on any given day, an average of nearly 8 workers on a line with roughly 55 home-line workers hails from a state celebrating some major, government recognized festival that day.

In Table D1, we regress line-level efficiency on home line absenteeism. We find that even after accounting for most aggregate absenteeism shocks at the factory floor level by way of a broad array

[70]In our data, we do not know where workers are from, but we know the language they speak. Although dialects are highly segregated across the country, the workers may not necessarily originate from that state. Nevertheless, the workers are likely to celebrate the festivals from that state since language is highly associated with cultural events.

[71]To compile the festival dates, we relied on government sources as much as possible. We compiled the dates of every major festivals celebrated state-wise (that we could find). In most cases, state governments list the most important festivals of their respective state. In some cases however, all festivals, major and minor, were listed. In such case, we retained only the festivals for which there was an actual holiday mandated by the government. The celebration dates of most festivals change with the lunar calendar and they often are celebrated for a different length of time. We used Google history searches to find the dates of the festivals in 2013 and 2014.

[72]We also included major Muslim festivals since a minority of workers are Muslim. Muslim festival dates are common across the country, but the worker composition at the line level is still varied enough to make it hard for managers to anticipate all absenteeism due to festivals.

of fixed effects, a line's idiosyncratic absenteeism still impacts its productivity. Table D2 is the instrumental variable version of the specification presented in Table D1, column 3. The instrument is highly predictive of absenteeism as shown in the first stage panel and coefficients from the IV second stage are quite similar to the coefficients from the OLS regressions. This suggests that, conditional on the fixed effects included, idiosyncratic line-level daily absenteeism is as good as random. Indeed, the Hausman test statistic reported in the lower panel confirms that we cannot reject that the OLS and IV coefficients are the same.

To confirm that the relationship between workers present on the line and efficiency depicted in Figure 5, panel (b), is preserved when leveraging the variation in absenteeism derived from the instrument, we plot the reduced form relationship using a nonparametric IV fit in Figure D1. That is, we first compute the average efficiency at the line level by 1% bins of the percentage of workers on the line just as we did in Figure 5, panel (b). For each of these bins, we also construct the average number of home-line workers with a festival at the line level. Following (Chetverikov and Wilhelm, 2017), we let the efficiency depend on a flexible spline in the percentage of workers on the line. This flexible spline is in return being instrumented with a flexible spline in the number of home-line workers with a festival in a fashion similar to a 2SLS estimator. The dots in Figure D1 depict the uninstrumented relationship and the crosses depict the fitted values of the nonparametric IV estimator. We can see that instrumented pattern closely matches the raw pattern.

Table D1: Productivity losses from absenteeism

	Efficiency (q/target)		
	(1)	(2)	(3)
Percentage of Absenteeism	−0.3971 (0.0374)∗∗∗ [0.0381]∗∗∗	−0.4068 (0.0307)∗∗∗ [0.0311]∗∗∗	−0.4451 (0.0317)∗∗∗ [0.0321]∗∗∗
Observations	12737	12737	12737
Mean of Y	49.09	49.09	49.09
SD	15.85	15.85	15.85

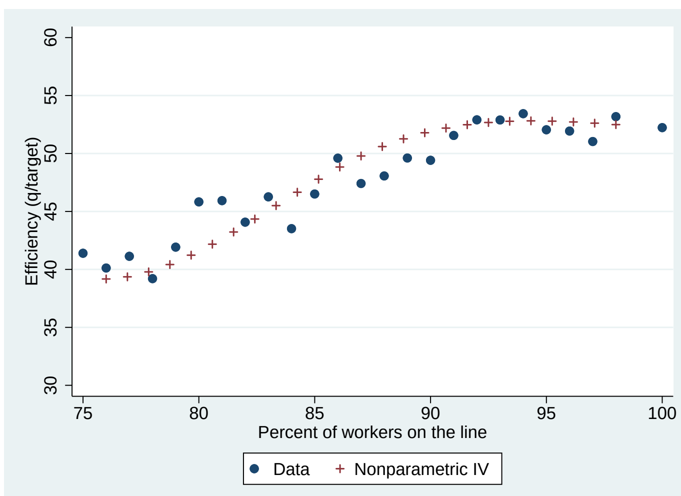
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress daily line-level efficiency on the line's percentage of absenteeism. Both variables are on a scale of 0-100. We cluster the standard errors reported in parentheses at the manager level. In square brackets, we report 2-way clustered standard errors with one cluster for managers and one for dates. In column 1, we include manager and unit fixed effects to absorb time-invariant characteristics of the managers and the units. In column 2 and 3, we also include year, month, and day of the week fixed effects to account for common seasonality and growth dynamics in productivity and absenteeism across units. In column 3, we also include fixed effects for the style of garments produced.

Table D2: Productivity losses from absenteeism with instrument

	IV-Second stage: Efficiency (%)
	(1)
Percentage of Workers Absent	−0.4814
	(0.2241)**
	[0.2514]*
	IV-First stage: Percentage of Workers Absent
Number of Workers with Festival	0.0255
	(0.0039)***
	[0.0054]***
Observations	10797
Mean of Y	49.086
SD	15.847
Kleibergen-Paap F	22.46
Hausman test p-value	.61

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We estimate a 2SLS with efficiency at the line day level as the dependent variable. Absenteeism at the line day level is the endogenous regressor that we instrument using the number of home-line workers with a festival that day. We cluster the standard errors reported in parentheses at the manager level and at the manager and date level in square brackets. We regress efficiency on the percentage of workers absent and we instrument this variable by the number of workers on the line with a festival that day.

Figure D1: Average efficiency by percentage of workers present on the line with nonparametric IV fit

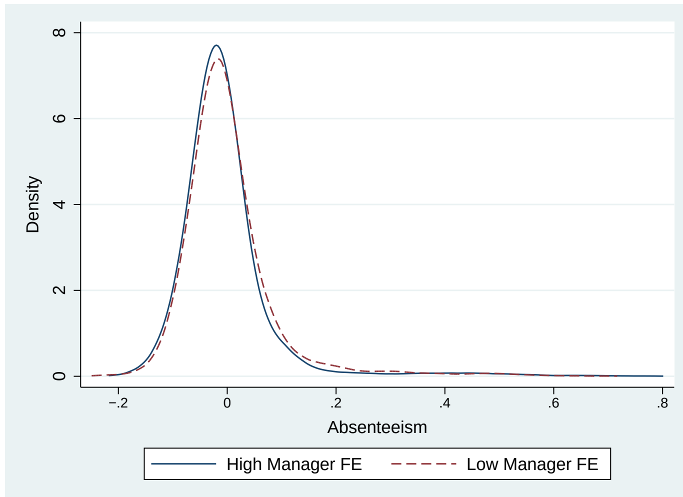


Note: We compute the average efficiency of the workers on the line and the average number of home-line workers with a festival by the percentage of workers working on the line (in 1% bins). The percentage of workers on the line is measured relative to the number of home-line workers available. We let the average efficiency depend on a spline with 3 equally-spaced knots in the average percentage of workers on the line. This spline is instrumented with a spline with 4 equally-spaced knots in the average number of home-line workers with a festival in a fashion similar to a 2SLS estimator. The dots depict the uninstrumented relationship and the crosses depict the fitted values of the nonparametric IV estimator. We exclude cases where the percentage of workers on the line falls below 75% or above 100% from the figure as these cases are infrequent.

Last, we check that the incidence of absenteeism shocks is balanced across lines and managers of varying quality. Using worker-by-day data, we recover manager (and worker) fixed effects through a decomposition in the spirit of (Abowd et al., 1999). To do so, we regress the log efficiency on unit, year, month, date, and style fixed effects and recover the manager component. We classify managers with a component higher or equal to the median as high-efficiency managers and those below the median as low-efficiency managers.

Then, in Figure D2, we partial out the same fixed effects from manager-day absenteeism and plot the distribution of residual absenteeism against the managers' efficiency status. "*Better*" and "*worse*" managers face nearly identical absenteeism shock distributions.

Figure D2: Distribution of residual absenteeism by manager FE



Note: Using worker-by-day data, we recover manager (and worker) fixed effects through a decomposition in the spirit of (Abowd et al., 1999). To do so, we regress the log efficiency on unit, year, month, date, and style fixed effects and recover the manager component. We classify managers with a component higher or equal to the median on their floor as high-efficiency managers and those below the median as low-efficiency managers. The manager at the median on odd floors is randomly assigned as a high- or low-quality manager. We partial out the same fixed effects from manager-day absenteeism and plot the distribution of residual absenteeism against the managers' efficiency status. Both types of managers have very similar absenteeism distributions. The mean residual absenteeism is -0.002 for high-efficiency managers and 0.004 for low-efficiency managers. The standard deviations are virtually identical (0.089).

E Model

We assume that each production line has the same number of home-line workers, $\bar{y}$, without loss of generality, and lines suffer from random absenteeism shocks. The production function of every line is increasing and concave in the number of workers on the line. Managers can borrow or lend workers from their main partners depending on the number of home-line workers present on their line and their partners' line, but contract enforcement is infeasible (Levin, 2003; MacLeod and Malcomson, 1989). There are two types of managers: reliable and unreliable. Managers privately know their own type and have a prior about their partner's type, which they update each period. Reliable managers always continue the ongoing relationship and unreliable managers exit the relational contract with an exogenous probability. We assume that there is a transaction cost, which affects the intensive and the extensive margin of the number of workers borrowed or lent. Finally, beliefs about main partners' types are updated following Bayes' rule. When all managers are reliable, the incentive compatibility constraint of the model clarifies how the number of home-line workers present, the outside option, and transaction costs affect the number of workers borrowed/lent between main partners. From this, we derive the regression equation described below. In a stationary relational contract the number of workers borrowed by manager i from manager j, (1) decreases as i's state (i.e., increases with absenteeism on i's line) improves (or i's absenteeism worsens) relatively to j's, and (2) increases as the transaction cost between i and j decreases; (3) moreover, it follows that as transaction costs decrease, the frequency of transfers between i and j increase. On the equilibrium path, as the maturity of the relationship (the cumulative number of transfers between managers i and j) increases, (1) the amount borrowed by manager i

from manager j also increases and, (2) the frequency of transfers between i and j increases.When managers are asymmetric (i.e., reliable and unreliable), on the transition path to a stationary contract with uncertainty over managerial type, the incentive compatibility constraint suggests a positive relationship between the number of workers borrowed or lent and the maturity of the relationship. Eventually, unreliable managers will be found out, and those relationships will end. In our data, relationship maturity is defined as the number of times a pair has exchanged workers. With at least 6 months of daily data, each pair can interact over 140 times, which allows us to track the evolution of managerial trading behavior over a large number of potential interactions.

We study a set of managers, $\mathscr{K}$, who live forever and share a common discount factor δ. Time is discrete, indexed by $t = 0, 1, ...$ Each production line has the same number of home-line workers, $\bar{y}$, and lines suffer from random absenteeism shocks. That is, in any given period, a certain number of these workers report for work (i.e., are present) – this quantity is denoted as $y_{i,t}$, where $y_{i,t} \in \mathscr{Y} \equiv \{y_1, y_2, \cdots, y_n\}$ and $y_1 < y_2 < \cdots < y_n$ with $y_n \equiv \bar{y}$.[73]

Each production line produces $f\left(y_{i,t} - \theta_{ij,t}\right)$ units of garments in period t, where $\theta_{ij,t}$ is the net number of workers transferred from manager i to manager j, and $f(\cdot)$ is a production function such that $f' > 0$ and $f'' < 0$ for all $y_{i,t} - \theta_{ij,t} > 0$.[74]

We assume that $y_{i,t}$ is publicly known and follows a Markov process with the probability of transition from state l to state k given by π^i_{lk}. We assume that a) $\pi^i_{lk} > 0$ for every pair of states $y_l, y_k \in \mathscr{Y}$ and for every manager $i \in \mathscr{K}$, b) there is some initial distribution over period 0, c) π^i_{lk} is independent across time and of the state of their peers, and d) distribution functions are symmetric, i.e., $\pi_i(\cdot) = \pi(\cdot)$ for every line $i \in \mathscr{K}$. From this set of assumptions, we obtain that $P(y_{i,t} = y_l, y_{j,t} = y_m) = P(y_{i,t} = y_l)P(y_{j,t} = y_m) = \pi(y_l)\pi(y_m)$ for every line i and $j \in \mathscr{K}$ and $l, m = 1, \cdots, n$, with l, m being the states associated with the number of home-line workers present. For simplicity, we denote this probability as π_{lm} and assume that $\pi(y_l) > 0$ for each $l = 1, \cdots, n$.

There are two types of managers: reliable (R) and unreliable (U). The measure of reliable managers is $\gamma_0 \in [0, 1]$, and the measure of unreliable managers is $1 - \gamma_0$.[75] Managers privately know their own type and have a prior about their partner's type γ_0, which they update each period.[76] Reliable managers always continue the ongoing relationship and unreliable managers exit the relational contract with probability $1 - \rho$. This probability is known to both parties and constant over time.[77]

[73]Our model is in essence similar to Coate and Ravallion (1993) and Ligon et al. (2002), but differs in two important ways: (i) hidden information is critical in our setting – we thus model private managerial type (reliable or unreliable); (ii) transaction costs of transferring workers affects both the intensive and extensive margins of trade.

[74]Note that the net number of workers transferred, $\theta_{ij,t}$, can be positive (lend workers) or negative (borrow workers).

[75]This is a fairly standard assumption in the relational contracting literature; see, e.g., Yang (2013), Halac (2012), and Malcomson (2016).

[76]Belief updating is explained in detail in Section H.2

[77]This leads to a simple (and fairly attractive) alternative interpretation for the model: suppose that there are two types of workers, having high and low productivity, respectively. Assume that low-productivity workers do not increase production, i.e., managers care only about high-productivity workers' absenteeism, which we can denote as $y_{i,t}$. Also assume that reliable and unreliable managers always tell the truth about the current number of high-productivity workers that they have. However, unreliable managers transfer $\theta_{ij,t}$ high-productivity workers with probability ρ, and transfer low-productivity workers (represented by $\theta_{ij,t} = 0$) with probability $1 - \rho$, whenever their state is better than their partner's. The model's analysis would proceed in the same manner, but could be interpreted as understanding the optimal flow of high-productivity workers in this context. This relates to several important papers in the theoretical relational contracting literature. For example, Yang (2013) studies non-stationary relational contracts in a repeated principal-agent game. That model is similar to ours in that workers can be of high or low type, but high-type workers

In period 0, managers are matched randomly and establish bilateral relationships. After each period, managers decide to continue or not in the bilateral relationship.[78] In a potentially ongoing relationship, manager i agrees to help manager j if i is in a better state (i.e., higher proportion of home-line workers present) than j; in return, j agrees to help i when their states are reversed in the future. At the end of the period managers confirm if their partner continue in the relationship, and decides to continue or not in the relationship.

Finally, we assume that there is a transaction cost, c, which does not depends on ij and is constant across states. Transaction costs affect the intensive margin i.e., the number of workers borrowed or lent. Contracts that are contingent on the state of the line, $y_{i,t}$, are not enforceable, and there is no information flow between matches. Moreover, we assume that a manager's history of transfers is not observable outside of a given match (i.e., to other fellow managers). Notice that having the Markov structure implies that the designing of an optimal relational contract will depend only on the current join state $(y_{i,t}, y_{j,t})$ and not on the past history that led to this state.

E.1 Timing

First, nature (N) matches every manager with a unique partner at $t = 0$. At the beginning of any period, nature selects the states of each production line, that is, $Y(t) = \left(y_{i,t}, y_{j,t}\right)$ for $i, j \in \mathscr{K}$, and U-type managers know if they will stay or not in the contract i.e., if they meet their partner this period, with exogenous probability. Then, after observing the history of the game, managers decide how many workers to lend. Managers meet and declare their state, and exchange workers. Finally, managers update their beliefs about their partner's type, period t ends and period $t+1$ begins.

For every $t \in \mathbb{N}_+$ and every pair of matched managers, an interaction will take place only if both managers decided to continue the relationship in the preceding periods (the managers have to participate when $t = 0$). Whenever a relationship is not over (in a period t) every couple of matched managers will play a stage game as follows:

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can choose a high effort $\bar{e} > 0$, while low-type workers exert low effort 0. Malcomson (2016) studies relational incentive contracts in a principal-agent setting where agents are heterogenous and have private information over their types. Malcomson's formulation differs from Yang's – among others – in that workers' types in the former model are continuously distributed.

[78]For simplicity of exposition, we posit that partnership formation is exogenous (i.e., manager pairs are determined randomly), and we also shut down experimentation. Note also that much of the canonical relational contract theory assumes quasi-linear utility and monetary transfers that can substitute for variation in continuation payoffs (Levin, 2003). Given our empirical context, it is natural to model risk averse agents; in this sense our model is positioned a bit closer to the literature on risk-sharing and informal insurance (Coate and Ravallion, 1993).

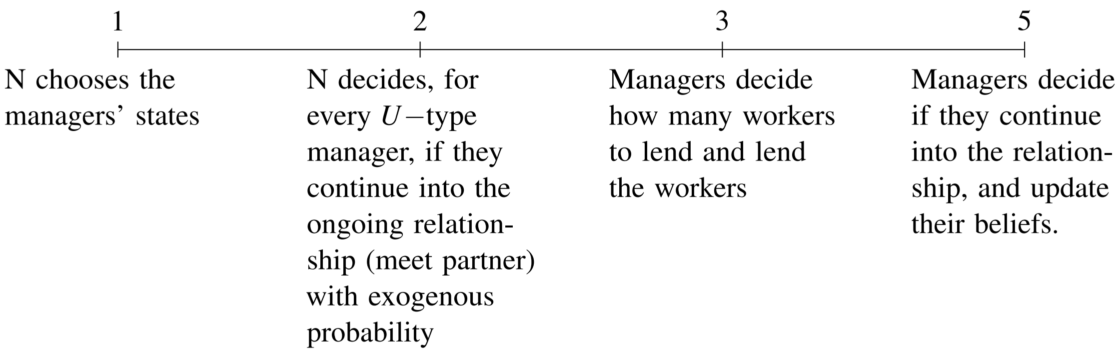


Figure E1: Stage game structure

This stage game structure is preserved for every $t > 0$ as long as both managers decide to keep the relational contract. If there is at least one manager who decided to dissolve the match in any t, the stage game becomes an autarchy for both managers for $t' > t$.

E.2 Strategies, belief updating, and incentive constraints

First of all, when it comes to managers' behavior, if the state of manager i is better than the state of j, there are three potential outcomes:

(1) If i is an R-type manager and transaction costs are low (compared to i's state), i chooses a transfer some of their own home-line workers to manager j, denoted as $\theta_{ij,t}$. Transfers are realized, and managers continue in the ongoing relationship.

(2) If i is an R-type manager and the transaction cost, c, is high (compared to i's state), i does not transfer any of their home-line workers to manager j, i.e., $\theta_{ij,t} = 0$. Then managers continue in the ongoing relationship.

(3) If manager i is a U-type, they exit with probability $1-\rho$. If i stays, the outcome can be (1) or (2).[79]

As the solution concept we adopt symmetric perfect public equilibrium (SPPE).[80] A strategy for a manager of type $u \in \{U, R\}$, σ^u, is a decision rule about whether to accept the current contract and the transfers to their partner as a function of the (within-dyad) history of transfers. A relational contract consists of a strategy profile $\sigma = \left(\sigma^R, \sigma^U\right)$.

In this section, we focus on a *reliable relational contract* in which managers help their partners over the long run (i.e., managers desire to interact only with R-type managers.) Thus, we restrict attention to the following trigger strategy: a manager continues in the relational contract if and only if the spot contract have always followed the equilibrium plan $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$, otherwise managers dissolve the match. Similar to Yang (2013), this trigger strategy prevents two types of reneging: a) managers' spot contract offer in period t can be different from the equilibrium transfer plan, and b) managers can stop the relationship even if their partners have always transferred the workers specified by the equilibrium path.

[79]Note that reliable managers and unreliable managers that tell the truth can shirk and quit the relationship in period t if the relational contract is no longer incentive compatible.

[80]We follow Yang (2013) in this solution concept. By symmetry, we mean that all managers adopt the same strategy. Public strategies require that each agents strategy only depends on the public history within the current relationship, since relationship history with previous partners is not observable.

Denote γ_t^{jj} as manager i's belief that their partner j is an R-type manager, given the history of t interactions. By Bayes' Rule, after t interactions from i to j, i's belief about the probability that j is an R-type is

$$\gamma_t^{jj} = \frac{\gamma_0}{\gamma_0 + \rho^t (1 - \gamma_0)}.$$

In an ongoing relationship, suppose i's reported state in period t is better than j's state. If i is an R-type manager, future payoffs from period t onward for a relationship are given by:

$$U_{i,t}^R \left(\boldsymbol{\theta}_t; \gamma_t^{jj} \right) = f \left(y_{i,t} - \theta_{ij,t} \right) - c_{ij} + \delta U_{i,t+1}^R \left(\boldsymbol{\theta}_{t+1}; \gamma_{t+1}^{jj} \right).$$

If i does not lend j workers, future payoffs from t onward for a relationship are given by

$$U_{i,t}^{S_r} \left(\boldsymbol{\theta}_t; \gamma_t^{jj} \right) = f \left(y_{i,t} \right) + \delta V \left(n_i \right),$$

where $V(n_i)$ is the outside option of manager i, which depends on the number of outside relationships, n_i.

The incentive compatibility constraint is thus:

$$f \left(y_{i,t} \right) - f \left(y_{i,t} - \theta_{ij,t} \right) + c_{ij} \leq \delta \left(U_{i,t+1}^R \left(\boldsymbol{\theta}_{t+1}; \gamma_{t+1}^{jj} \right) - V \left(n_i \right) \right). \tag{E.1}$$

The IC constraint for the U-type manager that on period t continues in the relationship is analogous:

$$f \left(y_{i,t} \right) - f \left(y_{i,t} - \theta_{ij,t} \right) + c_{ij} \leq \delta \left(U_{i,t+1}^U \left(\boldsymbol{\theta}_{t+1}; \gamma_{t+1}^{jj} \right) - V \left(n_i \right) \right). \tag{E.2}$$

Then, an *optimal dynamic reliable relational contract*, $\{\boldsymbol{\theta}_t^*\}_{t \in \mathbb{N}}$, is the maximum of $U_{i,0}^R (\{\boldsymbol{\theta}_t\}_t; \gamma_0)$ subject to the incentive compatibility constraints (E.1) for all t, where $U_{i,0}^R (\{\boldsymbol{\theta}_t\}_t; \gamma_0)$ is the present value of the expected utility over time, defined in equation (F.10).[81]

E.3 Symmetric stationary relational contracts

To study the features of a *symmetric stationary relational contract* in this context, suppose first that $\gamma_0 = 1$, that is, all managers are reliable so that they do not need to update their beliefs.[82] The incentive compatibility constraint in this case is thus

$$f \left(y_i \right) - f \left(y_i - \theta_{ij} \right) + c_{ij} \leq \delta \left(U^R \left(\boldsymbol{\theta} \right) - V \left(n_i \right) \right). \tag{E.3}$$

[81] Related work studies nonstationary relational contracts with a focus on informational aspects. For example, McAdams (2011) considers a model of partnerships in the form of complete information stochastic games with voluntary exit where payoffs are subject to a persistent initial shock—these shocks follow a general stochastic process. Under these hypotheses, the social welfare-maximizing equilibrium induces a dating process in which all parties enjoy full potential equilibrium gains. In contrast, shocks determining managers payoffs in our model follow a discrete distribution that is independent across time and states of different agents. Halac (2015) considers a principal-agent model where the principal makes an investment at the beginning of the relationship. The returns to this investment can be unobservable. The author shows that if the agent cannot observe the principals investment returns, then the agent cannot capture these returns.

[82] Note that if both managers are reliable, as $t \to \infty$, the relational contract converges with probability 1 to a *symmetric stationary relational contract*, in which both managers beliefs, γ_t^{jj}, converge to 1.

Let α_{ij} be the value of y_i for which equation (E.5) below is satisfied for positive values of θ_{ij}. The first-best allocation $\hat{\boldsymbol{\theta}}$, where each $\hat{\theta}_{ij} = \frac{y_i - y_j}{2}$ if $y_i > \max\{y_j, \alpha_{ij}\}$, and $\hat{\theta}_{ij} = 0$ in any other case, is the value of $\boldsymbol{\theta}$ that maximizes the function $U^R(\cdot)$ over the set of all possible allocations. Since the probabilities of observing a given state are symmetric across lines, we can restrict our search to the space of symmetric relational contracts where each $\boldsymbol{\theta} \in \mathbb{R}^{n^2}$ is characterized by a vector $\overrightarrow{\theta} = (\theta_{21}; \theta_{31}, \theta_{32}; \cdots; \theta_{n1}, \cdots, \theta_{nn-1}) \in \mathbb{R}^d$ with $d = n(n-1)/2$. The transfer in a stationary relational contract, $\boldsymbol{\theta}^*$, is such that it maximizes $U^R(\cdot)$ (see equation (F.1) in Appendix F) when restricting the domain to all symmetric non-negative allocations such that (E.3) is satisfied. Such a value $\boldsymbol{\theta}^*$ exists and it is unique because $U^R(\cdot)$ is strictly concave, and the restricted domain is a convex and compact subset of $\mathbb{R}^d$.[83]

Proposition 1. There exists a unique stationary contract $\boldsymbol{\theta}^*$ characterized by the following:

$$\theta^*_{ij} = \min\left\{\hat{\theta}_{ij}, H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)\right\}, \tag{E.4}$$

where $H(\cdot)$ is such that $\left(y_i, c_{ij}, w\right)$ satisfy

$$\Delta\left(y_i, c_{ij}, H\left(y_i, c_{ij}, w\right)\right) \equiv f(y_i) - f\left(y_i - H(y_i, c_{ij}, w)\right) + c_{ij} - w = 0, \tag{E.5}$$

with $w = \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)$, and $\hat{\theta}_{ij}$ is the first-best allocation.

Proposition 1 shows that given $y_i > y_j$ and c_{ij}, there exists a stationary equilibrium in which the optimal transfer for each y_i, c_{ij} is uniquely defined by (E.5). Note that the optimal transfer is always less than or equal to the efficient transfer, $\hat{\theta}_{ij}$.

From (E.5), it follows that the number of home-line workers transferred from i to j increases as the state of i increases, as long as the first-best allocation is never achieved. That is, as the state (proportion of home-line workers present) of line i increases, there is less pressure on the incentive constraint, which allows manager i to increase the number of workers transferred.

E.4 On the transition path to the stationary contract

If $\gamma_0 < 1$, note that if both managers are reliable, as $t \to \infty$, the relational contract converges with probability 1 to a *symmetric stationary relational contract*. From (E.1), it follows that on the transition path to steady state, as the number of transfers increases, the present value of the relationship, $U^R_{i,t+1}\left(\boldsymbol{\theta}_{t+1}; \gamma^{jj}_{t+1}\right)$, increases as well, since the posterior beliefs of partners being reliable increases. As a result, the number of workers transferred from line i to j (and vice versa) also increases. We present this result formally in the next proposition.

Proposition 2. There exists $\underline{\theta} > 0$ such that an optimal dynamic relational contract $\{\boldsymbol{\theta}^*_t\}_t$ is monotonic if $\theta^*_{ij,t} > \underline{\theta}$ for all $t \in \mathbb{N}$.

Proposition 2 shows that there exists a value $\underline{\theta} > 0$ such that if $\theta^*_{ij,t} > \underline{\theta}$, a *monotonic optimal dynamic relational contracts* arises if the allocation is below the first-best allocation defined above, i.e for all $t \in \mathbb{N}$, $\theta^*_{ij,t} < \hat{\theta}_{ij}$.[84] From the proof of Proposition 2 in Appendix F, it is easy to show

[83] For simplicity, we assume that the transaction costs between i and j are the same for both lines. Similarly, we assume that the outside option are the same for line i and j, i.e., $V \equiv V(n_i) = V(n_j)$.

[84] In the proof of Proposition 2 we show that $\underline{\theta}$ depends on the range of the y_i's. In particular, the larger the distance between the y_i's, the smaller the value of $\underline{\theta}$.

that given the value of γ_0, and conditions on ρ and δ, there is a period T after which $\theta^*_{ij,T+k}$ is monotonic for any $k \in \mathbb{N}$.[85]

If any manager (or both) is U-type, the relational contract will dissolve as $t \to \infty$. That is, the number of transfers may increase as the number of periods in which managers tell the truth increases (i.e., they borrow/lend workers from their partners or the difference in the lines' state does not compensate the transaction costs).[86] Eventually, U-type managers will be found out, and those relationships will end.[87]

To summarize, suppose that the number of home-line workers present for line j is greater than the number of home-line workers present for line i (i.e., $y_i < y_j$). Then, in a stationary relational contract the number of workers borrowed by manager i from manager j, (i) decreases as i's state (i.e., increases with absenteeism on i's line) improves (or i's absenteeism worsens) relatively to j's, and (ii) increases as the transaction cost between i and j decreases; (iii) moreover, it follows that as transaction costs decrease, the frequency of transfers between i and j increase. Finally, on the convergence path, as the maturity of the relationship (the cumulative number of transfers between managers i and j) increases, (i) the amount borrowed by manager i from manager j also increases and, (ii) the frequency of transfers between i and j increases.

F Proofs

Proof of proposition 1. A stationary symmetric optimal relational contract, $\boldsymbol{\theta}^*$, is defined as the the value of θ that maximizes $U^R(\cdot)$,

$$\begin{aligned}(1-\delta)U^R(\boldsymbol{\theta}) = & \sum_{\{(i,j)|y_i>\max\{y_j,\alpha_{ij}\}\}} \pi_{ij}\left[f(y_i-\theta_{ij})-c_{ij}\right] \\ & + \sum_{\{(i,j)|y_j>\max\{y_i,\alpha_{ij}\}\}} \pi_{ij}\left[f(y_i+\theta_{ji})\right] \\ & + \sum_{\{(i,j)|y_j\le y_i<\alpha_{ij}\vee y_i<y_j\le\alpha_{ij}\}} \pi_{ij} f(y_i),\end{aligned} \tag{F.1}$$

subject to the incentive compatibility constraint (E.3). The existence and uniqueness of $\boldsymbol{\theta}^*$ follows from the maximization of a concave function, $U^R(\cdot)$, over a compact convex subset of $\mathbb{R}^d$.

First, note that the concavity of $U^R(\cdot)$ follows from the concavity of f (i.e., $f'' < 0$), restricted to all symmetric non-negative allocations such that (E.3) is satisfied. Second, note that the domain,

[85] Note that, in general, dynamic relational contracts are quasi-monotonic (see, e.g., Yang (2013)).

[86] Board (2011) studies a game in which a principal and a set of agents trade over time under the threat of holdup. He shows that the optimal relational contract induces loyalty (i.e., the principal is loyal to the agents they have traded with, while being biased against new agents).

[87] Note that U-type managers can exit the relationship if their continuation value does not satisfy the IC constraint. Moreover, we assume that managers are not sophisticated and anticipate the existence of a period $T^*(y_i, y_j)$ after which managers are reliable almost surely.

$$\Omega := [-\bar{y},\bar{y}]^d \cap \left[\cap_{i=1}^{n} \cap_{j=1}^{i-1} \underbrace{\left\{ \theta_{ij} \in \mathbb{R}^d | f(y_i) - f\left(y_i - \theta_{ij}\right) + c_{ij} \leq \delta\left(U^R(\boldsymbol{\theta}) - V\right) \right\}}_{=:A} \right],$$

is a convex and compact subset of $\mathbb{R}^d$ since A is closed and convex.

To characterize $\boldsymbol{\theta}^*$, let $H(y,c,w)$ a function implicitly defined by

$$f(y) + c - w = f(y - H(y,c,w)). \tag{F.2}$$

Note that $f'(\cdot) > 0$, then $H(\cdot)$ can be expressed as

$$H(y,c,w) = y - f^{-1}(c - w + f(y)), \tag{F.3}$$

for all the values (y,c,w) for which $c - w + f(y) > 0$. Given y_i, c_{ij} and $\delta\left(U^R(\boldsymbol{\theta}^*) - V\right)$ then $H(\cdot)$ is such that

$$f(y_i) - f\left(y_i - H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right) \right) + c_{ij} = \delta\left(U^R(\boldsymbol{\theta}^*) - V\right), \tag{F.4}$$

as long as

$$f(y_i) + c_{ij} > \delta\left(U^R(\boldsymbol{\theta}^*) - V\right) \tag{F.5}$$

is satisfied. Therefore, $\theta_{ij}^* = H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$ if (F.5) is satisfied.

Now we show that $\theta_{ij}^* = \min\left\{\hat{\theta}_{ij}, H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)\right\}$. We split the proof in two cases: *i*) suppose that $\hat{\theta}_{ij} > H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$, then in this case we show that $\theta_{ij}^* = H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$; *ii*) suppose that $\hat{\theta}_{ij} \leq H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$ then we show that $\theta_{ij}^* = \hat{\theta}_{ij}$.

i) Suppose that $\hat{\theta}_{ij} > H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$. Since $H(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)) = y_i - f^{-1}(c_{ij} - \delta\left(U^R(\boldsymbol{\theta}^*) - V\right) + f(y_i))$ it follows that

$$\begin{aligned} \hat{\theta}_{ij} > H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right) &\iff \\ \hat{\theta}_{ij} > y_i - f^{-1}(c_{ij} - \delta\left(U^R(\boldsymbol{\theta}^*) - V\right) + f(y_i)) &\iff \\ c_{ij} - \delta\left(U^R(\boldsymbol{\theta}^*) - V\right) + f(y_i) > f(y_i - \hat{\theta}_{ij}) &\iff \\ f(y_i) - f(y_i - \hat{\theta}_{ij}) + c_{ij} > \delta\left(U^R(\boldsymbol{\theta}^*) - V\right). & \end{aligned}$$

Note that $f > 0$, then

$$f(y_i) + c_{ij} > \delta\left(U^R(\boldsymbol{\theta}^*) - V\right).$$

Thus, (F.5) is satisfied, and we conclude that $\theta_{ij}^* = H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$.

ii) Suppose that $\hat{\theta}_{ij} \leq H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)$. From the definition of $H(\cdot)$ we get

$$\begin{aligned}
\hat{\theta}_{ij} \leq H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right) &\iff \\
\hat{\theta}_{ij} \leq y_i - f^{-1}(c_{ij} - \delta\left(U^R(\boldsymbol{\theta}^*) - V\right) + f(y_i)) &\iff \\
c_{ij} - \delta\left(U^R(\boldsymbol{\theta}^*) - V\right) + f(y_i) \leq f(y_i - \hat{\theta}_{ij}) &\iff \\
f(y_i) - f(y_i - \hat{\theta}_{ij}) + c_{ij} \leq \delta\left(U^R(\boldsymbol{\theta}^*) - V\right).&
\end{aligned}$$

Therefore, the contract defined by $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ belongs to the set Ω.[88] Note that

$$\frac{\partial U^R(\boldsymbol{\theta})}{\partial \theta_{ij}} > (<) 0 \text{ if } \theta_{ij} < (>) \hat{\theta}_{ij}. \tag{F.6}$$

Thus, if $\theta^*_{ij} < \hat{\theta}_{ij}$ then $U^R(\boldsymbol{\theta}^*) < U^R(\boldsymbol{\theta}^*/\hat{\theta}_{ij})$. If $\theta^*_{ij} > \hat{\theta}_{ij}$ then $U^R(\boldsymbol{\theta}^*) < U^R(\boldsymbol{\theta}^*/\hat{\theta}_{ij})$. Note that $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ yields a larger utility than $\boldsymbol{\theta}^*$, with $\boldsymbol{\theta}^*/\hat{\theta}_{ij} \in \Omega$, which is a contradiction. Therefore, $\theta^*_{ij} = \hat{\theta}_{ij}$.

Thus, we conclude that that $\theta^*_{ij} = \min\left\{\hat{\theta}_{ij}, H\left(y_i, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right)\right\}$.

Proof of proposition 2. An optimal dynamic relational contract, $\{\boldsymbol{\theta}^*_t\}_{t\in\mathbb{N}}$, is defined as the value of $\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}$ that maximizes $U^R_0(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0)$ subject to the incentive compatibility constraints (E.1) for all t, where $U^R_0(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0)$ is the present value of the expected utility over time, defined in equation (F.10). We show that there exists $\underline{\theta} > 0$ such that if $\{\boldsymbol{\theta}^*_t\}_{t\in\mathbb{N}}$ is an optimal dynamic relational contract satisfying that for any $i, j \in \mathscr{K}$, and for every $t \in \mathbb{N}$, $\theta^*_{ij,t} \in (\underline{\theta}, \hat{\theta}_{ij})$, then $\{\boldsymbol{\theta}^*_t\}_{t\in\mathbb{N}}$ must be monotonic.[89]

We divide the proof in two steps: 1) we find an expression for the present value of the expected utility over time at time t, $U^R_t(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$; 2) we show that $U^R_t(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ is increasing with respect to γ_t.[90]

1) Given a relational contract $\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}$ and the beliefs at time t, γ_t, an R-type manager's expected utility after t periods is

$$\begin{aligned}
U_t(\boldsymbol{\theta}_t; \gamma_t) = {} & (\gamma_t + (1-\gamma_t)\rho)\left[\sum_{S_1} \pi_{ij}\left(f\left(y_{i,t} - \theta_{ij,t}\right) - c_{ij}\right) + \sum_{S_2} \pi_{ij} f\left(y_{i,t} + \theta_{ji,t}\right)\right] \\
& + (1-\gamma_t)(1-\rho)\left[\sum_{S_1\cup S_2} \pi_{ij} f\left(y_{i,t}\right)\right] + \sum_{S_3\cup S_4} \pi_{ij} f\left(y_{i,t}\right) \\
& + (1-\gamma_t)(1-\rho)\delta V + (\gamma_t + (1-\gamma_t)\rho)\delta U_{t+1}(\boldsymbol{\theta}_{t+1}; \gamma_{t+1}),
\end{aligned} \tag{F.7}$$

[88] $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ is notation for the vector $\boldsymbol{\theta}^*$ in which the θ^*_{ij} is replaced by $\hat{\theta}_{ij}$

[89] A dynamic relational contract $\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}$ is monotonic if for for any $i, j \in \mathscr{K}$, and for every $t \in \mathbb{N}$, $\theta_{ij,t} \leq \theta_{ij,t+1}$.

[90] Note that in this proof we are using the fact that both the beliefs γ^{ij}_t and the probabilities π_{ij} are symmetric. Thus, we omit the index i in the utility of an R-type manager.

where $S_1 \equiv \{(i,j)|y_{i,t} > \max\{y_{j,t}, \alpha_{ij,t}\}\}$, $S_2 \equiv \{(i,j)|y_{j,t} > \max\{y_{i,t}, \alpha_{ji,t}\}\}$, $S_3 \cup S_4 \equiv \{(i,j)|y_{j,t} \leq y_{i,t} < \alpha_{ij,t}\} \cup \{(i,j)|y_{i,t} < y_{j,t} \leq \alpha_{ji,t}\}$, and $\alpha_{ij,t}$ is the value of y_i such that

$$f(y_i) - f(y_i - \theta_{ij,t}) + c_{ij} - \delta \left(U^R_{t+1}(\boldsymbol{\theta}_{t+1}; \gamma_{t+1}) - V\right) = 0, \tag{F.8}$$

is satisfied for positive values of $\theta_{ij,t}$ and $\theta_{ij,t+1}$.[91]

To simplify the notation let

$$\tilde{\gamma}_t = \gamma_t + (1-\gamma_t)\rho \quad \text{and} \quad 1 - \tilde{\gamma}_t = (1-\gamma_t)(1-\rho).$$

To find $U^R_t(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$, we will recursively apply (F.7). The term $\tilde{\gamma}_t$ in the expression (F.7) is capturing R-type manager's utility when interacting with the mass of reliable managers γ_t, and the mass of unreliable managers telling the true $(1-\gamma_t)(1-\rho)$. Then, $U^R_t(\boldsymbol{\theta}_t; \gamma_t)$ can be expressed as

$$U^R_t(\boldsymbol{\theta}_t; \gamma_t) = \tilde{\gamma}_t F(\boldsymbol{\theta}_t) + C(V; \gamma_t) + g(\mathbf{y}; \gamma_t) + \tilde{\gamma}_t \delta U^R_{t+1}(\boldsymbol{\theta}_{t+1}; \gamma_{t+1}), \tag{F.9}$$

where

$$\begin{aligned}
F(\boldsymbol{\theta}_t) &\equiv \sum_{S_1} \pi_{ij}\left[f\left(y_i - \theta_{ij,t}\right) + f\left(y_i + \theta_{ji,t}\right)\right], \\
C(V; \gamma_t) &\equiv -\tilde{\gamma}_t \sum_{S_1} \pi_{ij} c_{ij} + (1-\tilde{\gamma}_t)\delta V, \text{ and} \\
g(\mathbf{y}; \gamma_t) &\equiv 2(1-\tilde{\gamma}_t) \sum_{S_1} \pi_{ij}\left[f(y_i)\right] + \sum_{S_3 \cup S_4} \pi_{ij} f(y_i).
\end{aligned}$$

Note that (F.9) follows from: (i) $\pi_{ij} = \pi_{ji}$ for all $i,j \in \mathscr{K}$; (ii) $\pi_{ij} = \mathbb{P}(y_{i,t} = y_i)\mathbb{P}(y_{j,t} = y_j)$ for each t; (iii) since beliefs are symmetric $\alpha_{ij,t} = \alpha_{ji,t}$ and $S_1 = S_2$. Now, we successively use (F.9) to obtain an explicit equation for $U^R_t(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$. Note that after two iterations we have

$$\begin{aligned}
U^R_t(\boldsymbol{\theta}_t; \gamma_t) =& \tilde{\gamma}_t \left[F(\boldsymbol{\theta}_t) + \delta\tilde{\gamma}_{t+1} F(\boldsymbol{\theta}_{t+1}) + \delta^2 \tilde{\gamma}_{t+1}\tilde{\gamma}_{t+2} F(\boldsymbol{\theta}_{t+2})\right] \\
&+ \left[C(V; \gamma_t) + \delta\tilde{\gamma}_t C(V; \gamma_{t+1}) + \delta^2 \tilde{\gamma}_t \tilde{\gamma}_{t+1} C(V; \gamma_{t+2})\right] \\
&+ \left[g(\mathbf{y}; \gamma_t) + \delta\tilde{\gamma}_t g(\mathbf{y}; \gamma_{t+1}) + \delta^2 \tilde{\gamma}_t \tilde{\gamma}_{t+1} g(\mathbf{y}; \gamma_{t+2})\right] + \tilde{\gamma}_t \tilde{\gamma}_{t+1} \tilde{\gamma}_{t+2} \delta^3 U^R_{t+3}(\boldsymbol{\theta}_{t+3}; \gamma_{t+3}) + \cdots
\end{aligned}$$

Thus, the present value of the expected utility at time t is

$$U^R_t(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t) = \sum_{k=0}^{\infty} \delta^k \Gamma_t^{k-1}\left[\tilde{\gamma}_{t+k} F(\boldsymbol{\theta}_{t+k}) + C(V; \gamma_{t+k}) + g(\mathbf{y}; \gamma_{t+k})\right], \tag{F.10}$$

where $\Gamma^k_t := \prod_{l=0}^k \tilde{\gamma}_{t+l}$, and $\Gamma_t^{-1} := 1$.

2) We show now that $U^R_t(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ is increasing with respect to γ_t. First, note that $F(\cdot)$ has

[91] At time t, the set S_1 (S_2) is the set of states of manager i (j) better than the state of manager j (i) and high enough to compensate for the transaction costs; S_3 (S_4) is the set of states of manager i (j) better than the states of manager j (i), but are not high enough to compensate for the transaction costs, thus, there are no trades.

a global maximum at $\theta_{ij,t} = \hat{\theta}_{ij}$, thus, for any $(i,j) \in S_1$

$$\frac{\partial F(\boldsymbol{\theta}_t)}{\partial \theta_{ij,t}} > (<)\, 0 \;\text{ if }\; \theta_{ij,t} < (>)\, \hat{\theta}_{ij}. \tag{F.11}$$

Therefore, $F(\boldsymbol{\theta}_t)$ is strictly positive and bounded above by $F(\hat{\boldsymbol{\theta}})$. Second, note that for any $k, t \in \mathbb{N}$ the following facts hold true:

$$\begin{aligned}
&\text{(i) } \gamma_t = \frac{\gamma_0}{\gamma_0 + \rho^t (1-\gamma_0)}.\\
&\text{(ii) Let } h^k(x) = \frac{x}{x + (1-x)\rho}. \text{ Then } \gamma_{t+k} = h^k(\gamma_t) = \cdots = h^{k+t}(\gamma_0).\\
&\text{(iii) From the definition of } \tilde{\gamma}_{t+k}, \text{and the fact } h'(\cdot) > 0,\; \frac{\partial \tilde{\gamma}_{t+k}}{\partial \gamma_t} = \rho \frac{\partial h^k(\gamma_t)}{\partial \gamma_t} > 0.\\
&\text{(iv) Since } \ln \Gamma_t^k = \sum_{l=0}^{k} \ln \tilde{\gamma}_{t+l}, \text{ then } \frac{\partial \Gamma_t^k}{\partial \gamma_t} = \Gamma_t^k \sum_{l=0}^{k} \frac{1}{\tilde{\gamma}_{t+l}} \frac{\partial \tilde{\gamma}_{t+l}}{\partial \gamma_t} > 0.
\end{aligned} \tag{F.12}$$

The derivative of $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ with respect to γ_t is another series with the k-term equal to

$$\begin{aligned}
&\frac{\partial}{\partial \gamma_t} \left\{ \Gamma_t^{k-1} \left[\tilde{\gamma}_{t+k} F(\boldsymbol{\theta}_{t+k}) + C(V; \gamma_{t+k}) + g(\mathbf{y}; \gamma_{t+k}) \right] \right\}\\
&= \Gamma_t^{k-1} \left(\sum_{l=0}^{k} \frac{\tilde{\gamma}_{t+k}}{\tilde{\gamma}_{t+l}} \frac{\partial \tilde{\gamma}_{t+l}}{\partial \gamma_t} \right) \left(\sum_{S_1} \pi_{ij} \left[f\left(y_i - \theta_{ij,t+k}\right) + f\left(y_i + \theta_{ji,t+k}\right) - 2f(y_i) - c_{ij} \right] \right)\\
&+ \Gamma_t^{k-1} \left(\sum_{l=0}^{k-1} \frac{(1-\tilde{\gamma}_{t+k})}{\tilde{\gamma}_{t+l}} \frac{\partial \tilde{\gamma}_{t+l}}{\partial \gamma_t} - \frac{\partial \tilde{\gamma}_{t+k}}{\partial \gamma_t} \right) \delta V + \Gamma_t^{k-1} \left(\sum_{l=0}^{k-1} \frac{1}{\tilde{\gamma}_{t+l}} \frac{\partial \tilde{\gamma}_{t+l}}{\partial \gamma_t} \right) E_{\pi_{ij}}[f(y_i)]
\end{aligned} \tag{F.13}$$

where $E_{\pi_{ij}}[f(y_i)] = 2\sum_{S_1} \pi_{ij}[f(y_i)] + \sum_{S_3 \cup S_4} \pi_{ij} f(y_i)$.[92]

From (iii) and (iv) in (F.12), expression (F.13), is positive for any $k \in \mathbb{N} \cup \{0\}$ as long as

$$\sum_{S_1} \pi_{ij} \left[f\left(y_i - \theta_{ij,t+k}\right) + f\left(y_i + \theta_{ji,t+k}\right) - 2f(y_i) - c_{ij} \right] - \delta V > 0. \tag{F.15}$$

Now, the left hand side of (F.15) is strictly increasing with respect to the variable $\theta_{ij,t+k}$, as long as $\theta_{ij,t+k} < \hat{\theta}_{ij}$. Moreover, if $\theta_{ij,t+k} = \hat{\theta}_{ij}$ the left hand side of (F.15) is

$$\sum_{S_1} \pi_{ij} \left[f\left(y_i - \hat{\theta}_{ij}\right) + f\left(y_i + \hat{\theta}_{ij}\right) - 2f(y_i) - c_{ij} \right] - \delta V > 0. \tag{F.16}$$

[92] Note that for $k = 0$, (F.13) is

$$\begin{aligned}
&\frac{\partial}{\partial \gamma_t} \left[\tilde{\gamma}_t F(\boldsymbol{\theta}_t) + C(V; \gamma_t) + g(\mathbf{y}; \gamma_t) \right]\\
&= (1-\rho) \sum_{S_1} \pi_{ij} \left[f(y_i - \theta_{ij,t}) + f(y_i + \theta_{ji,t}) - 2f(y_i) - c_{ij} \right] - (1-\rho)\delta V.
\end{aligned} \tag{F.14}$$

By continuity there exists a constant $\underline{\theta}$, independent of k, such that for any $\theta_{ij,t+k} \in (\underline{\theta}, \hat{\theta}_{ij})$, (F.15) holds. Which proves that expression (F.13) is positive for any $k \in \mathbb{N} \cup \{0\}$, thus, $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ is strictly increasing with respect to γ_t.

Finally, if $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ is an optimal dynamic relational contract satisfying that for any $i, j \in \mathscr{K}$, and for every $t \in \mathbb{N}$, $\theta_{ij,t}^* \in (\underline{\theta}, \hat{\theta}_{ij})$, then $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ is a maximum of the function $U_0^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0)$ subject to the IC constraints. Note that the IC constraint increases at every step t, then by the monotonicity of $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ and (F.11), $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ must be monotonic.

G Extensive margin and robustness to using all dyads

Table G1: Empirical tests for the extensive margin

	Any number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	568.7733	124.3410	120.7499
	(0.0241)$**$	(0.0446)$**$	(0.0431)$**$
	[0.0237]$**$	[0.0445]$**$	[0.0432]$**$
	{0.1166}	{0.1130}	{0.1081}
log(Maturity of relationship)	1.8444	4.4665	4.4677
	(0.0000)$***$	(0.0000)$***$	(0.0000)$***$
	[0.0000]$***$	[0.0000]$***$	[0.0000]$***$
	{0.0000}$***$	{0.0000}$***$	{0.0000}$***$
log(Distance)	0.4655	0.7898	0.7898
	(0.0000)$***$	(0.0222)$**$	(0.0221)$**$
	[0.0000]$***$	[0.0308]$**$	[0.0322]$**$
	{0.0000}$***$	{0.1026}	{0.1033}
	Identity-based distance		
Different gender	0.4685	0.4726	0.4724
	(0.0060)$***$	(0.0027)$***$	(0.0027)$***$
	[0.0066]$***$	[0.0026]$***$	[0.0025]$***$
	{0.0980}$*$	{0.0979}$*$	{0.0976}$*$
Different education	0.5920	0.7351	0.7352
	(0.0000)$***$	(0.0044)$***$	(0.0044)$***$
	[0.0001]$***$	[0.0111]$**$	[0.0125]$**$
	{0.0000}$***$	{0.0072}$***$	{0.0073}$***$
log(Difference in age of managers)	0.9712	0.9554	0.9555
	(0.1248)	(0.0176)$**$	(0.0175)$**$
	[0.1447]	[0.0234]$**$	[0.0237]$**$
	{0.1885}	{0.0397}$**$	{0.0405}$**$
log(Diff. in exp. on the line)	0.8493	0.7934	0.7934
	(0.0882)$*$	(0.0102)$**$	(0.0102)$**$
	[0.0885]$*$	[0.0104]$**$	[0.0103]$**$
	{0.0937}$*$	{0.0263}$**$	{0.0261}$**$
Observations	28813	28813	28813
Mean of Y	.188	.188	.188
SD	.176	.176	.176

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress a dummy for whether *i* borrows any number worker from *j* at the daily manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report *p-values* for standard errors clustered at the pair level. In square brackets, we report *p-values* for 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report *p-values* for 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table G2: Empirical tests keeping all dyads

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	5.7479	4.8996	4.5722
	(2.1266)∗∗∗	(2.1049)∗∗	(2.0348)∗∗
	[2.1254]∗∗∗	[2.1064]∗∗	[2.0381]∗∗
	{2.6984}∗∗	{2.3987}∗∗	{2.3589}∗
log(Maturity of relationship)	0.4063	1.2654	1.2694
	(0.1093)∗∗∗	(0.0789)∗∗∗	(0.0787)∗∗∗
	[0.1104]∗∗∗	[0.0787]∗∗∗	[0.0785]∗∗∗
	{0.1163}∗∗∗	{0.0845}∗∗∗	{0.0843}∗∗∗
log(Distance)	−0.7789	−0.2664	−0.2643
	(0.1137)∗∗∗	(0.0785)∗∗∗	(0.0784)∗∗∗
	[0.1151]∗∗∗	[0.0795]∗∗∗	[0.0795]∗∗∗
	{0.1279}∗∗∗	{0.0976}∗∗∗	{0.0976}∗∗∗
	Identity-based distance		
Different gender	−0.7767	−0.8749	−0.8758
	(0.3371)∗∗	(0.3315)∗∗∗	(0.3314)∗∗∗
	[0.3341]∗∗	[0.3307]∗∗∗	[0.3308]∗∗∗
	{0.2465}∗∗∗	{0.2909}∗∗∗	{0.2910}∗∗∗
Different education	−0.4178	−0.1219	−0.1211
	(0.1371)∗∗∗	(0.0877)	(0.0875)
	[0.1374]∗∗∗	[0.0870]	[0.0869]
	{0.1431}∗∗∗	{0.1017}	{0.1020}
log(Difference in age of managers)	−0.0131	−0.0271	−0.0271
	(0.0172)	(0.0136)∗∗	(0.0136)∗∗
	[0.0172]	[0.0136]∗∗	[0.0136]∗∗
	{0.0176}	{0.0145}∗	{0.0146}∗
log(Diff. in exp. on the line)	−0.0637	−0.1474	−0.1469
	(0.0944)	(0.0655)∗∗	(0.0655)∗∗
	[0.0937]	[0.0649]∗∗	[0.0649]∗∗
	{0.0783}	{0.0651}∗∗	{0.0650}∗∗
Observations	47847	47847	47847
Mean of Y	.24	.24	.24
SD	.928	.928	.928
Effect when X1= 1%	5.92 %	5.02 %	4.68 %
Effect when X1= 5%	33.29 %	27.76 %	25.69 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. All dyads that are on a same floor are included. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

In the main results section of the paper, we keep only dyads where $(\frac{\%Abs\,i - \%Abs\,j}{2}) \geq 0$. In table G2, we keep all dyads and the main regressor is equal to $(\frac{\%Abs\,i - \%Abs\,j}{2})$ whenever $(\frac{\%Abs\,i - \%Abs\,j}{2}) \geq 0$ and is equal to 0 otherwise. In order not to drop dyads, we control for a dummy variable equal to 1 when $(\frac{\%Abs\,i - \%Abs\,j}{2}) < 0$ and 0 otherwise. The results are very similar to what we found before.

Table G3: Empirical tests controlling for whether managers in a dyad work on the same style of garment

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	5.9146	5.3276	4.9737
	(2.0679)∗∗∗	(1.7867)∗∗∗	(1.6948)∗∗∗
	[2.0764]∗∗∗	[1.8015]∗∗∗	[1.7172]∗∗∗
	{2.5763}∗∗	{2.0094}∗∗∗	{1.9408}∗∗
log(Maturity of relationship)	0.3474	1.3107	1.3140
	(0.1186)∗∗∗	(0.0868)∗∗∗	(0.0864)∗∗∗
	[0.1201]∗∗∗	[0.0877]∗∗∗	[0.0872]∗∗∗
	{0.1357}∗∗	{0.0929}∗∗∗	{0.0927}∗∗∗
log(Distance)	−0.8458	−0.2554	−0.2544
	(0.1181)∗∗∗	(0.0835)∗∗∗	(0.0832)∗∗∗
	[0.1194]∗∗∗	[0.0853]∗∗∗	[0.0850]∗∗∗
	{0.1281}∗∗∗	{0.0917}∗∗∗	{0.0914}∗∗∗
	Identity-based distance		
Different gender	−0.9614	−1.0094	−1.0118
	(0.2392)∗∗∗	(0.2099)∗∗∗	(0.2123)∗∗∗
	[0.2334]∗∗∗	[0.2060]∗∗∗	[0.2089]∗∗∗
	{0.3384}∗∗∗	{0.3559}∗∗∗	{0.3581}∗∗∗
Different education	−0.5029	−0.1836	−0.1838
	(0.1288)∗∗∗	(0.0915)∗∗	(0.0913)∗∗
	[0.1305]∗∗∗	[0.0923]∗∗	[0.0923]∗∗
	{0.1255}∗∗∗	{0.0816}∗∗	{0.0812}∗∗
log(Difference in age of managers)	−0.0272	−0.0474	−0.0476
	(0.0187)	(0.0157)∗∗∗	(0.0157)∗∗∗
	[0.0186]	[0.0156]∗∗∗	[0.0156]∗∗∗
	{0.0193}	{0.0162}∗∗∗	{0.0164}∗∗∗
log(Diff. in exp. on the line)	−0.1736	−0.2720	−0.2711
	(0.0977)∗	(0.0790)∗∗∗	(0.0789)∗∗∗
	[0.0967]∗	[0.0778]∗∗∗	[0.0776]∗∗∗
	{0.0787}∗∗	{0.0806}∗∗∗	{0.0804}∗∗∗
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	6.09 %	5.47 %	5.10%
Effect when X1= 5%	34.41 %	30.52 %	28.23 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. In all specifications, we include a dummy variable equal to one if the two managers in the dyad work on the same style of garment. All dyads that are on a same floor are included. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

H Quality

Here, we show that there is heterogeneity in trade behavior with regards to worker "quality." Instead of looking at the aggregate number of workers borrowed (as in the previous analysis), we separated workers by whether their efficiency is below or above the median. To group the workers into efficiency quartiles, we first net their daily efficiency of unit, line, garment style, and date fixed effects. Then, we compute the workers' average (residual) efficiency over the span of the data.

Table H1: Lower efficiency workers

	Nb. Below Med. eff.		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	6.2394	5.7413	5.6716
	(1.3226) ∗∗∗	(1.3434) ∗∗∗	(1.3146) ∗∗∗
	[1.3050] ∗∗∗	[1.3269] ∗∗∗	[1.2967] ∗∗∗
	{1.6472} ∗∗∗	{1.5434} ∗∗∗	{1.5400} ∗∗∗
log(Maturity of relationship)	2.1077	1.6512	1.6343
	(0.5689) ∗∗∗	(0.4664) ∗∗∗	(0.4603) ∗∗∗
	[0.5790] ∗∗∗	[0.4657] ∗∗∗	[0.4595] ∗∗∗
	{0.6277} ∗∗∗	{0.4838} ∗∗∗	{0.4763} ∗∗∗
log(Maturity of relationship)^2	−0.2427	−0.0371	−0.0343
	(0.0844) ∗∗∗	(0.0674)	(0.0665)
	[0.0859] ∗∗∗	[0.0674]	[0.0665]
	{0.0959} ∗∗	{0.0709}	{0.0698}
log(Distance)	−0.6763	−0.0586	−0.0579
	(0.1437) ∗∗∗	(0.1315)	(0.1313)
	[0.1443] ∗∗∗	[0.1317]	[0.1316]
	{0.1578} ∗∗∗	{0.1490}	{0.1487}
	Identity-based distance		
Different gender	−0.8434	−0.8697	−0.8685
	(0.4078) ∗∗	(0.3682) ∗∗	(0.3695) ∗∗
	[0.4074] ∗∗	[0.3707] ∗∗	[0.3722] ∗∗
	{0.3883} ∗∗	{0.4035} ∗∗	{0.4026} ∗∗
Different education	−0.3788	−0.0709	−0.0703
	(0.1732) ∗∗	(0.1417)	(0.1417)
	[0.1723] ∗∗	[0.1406]	[0.1407]
	{0.1803} ∗∗	{0.1559}	{0.1558}
log(Difference in age of managers)	−0.0168	−0.0285	−0.0283
	(0.0240)	(0.0218)	(0.0217)
	[0.0242]	[0.0218]	[0.0218]
	{0.0255}	{0.0219}	{0.0219}
log(Diff. in exp. on the line)	−0.2001	−0.2137	−0.2142
	(0.1228)	(0.1113)∗	(0.1112)∗
	[0.1210]∗	[0.1090] ∗∗	[0.1088] ∗∗
	{0.1237}	{0.1193}∗	{0.1194}∗
Observations	29091	29091	29091
Mean of Y	.098	.098	.098
SD	.462	.462	.462
Effect when X1= 1%	6.44 %	5.91 %	5.84 %
Effect when X1= 5%	36.61 %	33.25 %	32.79 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of below-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of these workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of below-median efficiency workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

In Table H1, we regress the number of lower-efficiency workers borrowed on the difference in absenteeism of lower-efficiency workers in the dyad that day and the same controls as in our main specifications.[93] We show the corresponding results for higher-efficiency workers in Table H2.[94]

Table H2: Higher-efficiency workers

	Nb. above Med. eff.		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	2.8437	2.9186	2.7279
	(1.5386)∗	(1.2620)∗∗	(1.1979)∗∗
	[1.5450]∗	[1.2713]∗∗	[1.2124]∗∗
	{1.7882}	{1.3863}∗∗	{1.3062}∗∗
log(Maturity of relationship)	3.0446	2.6004	2.6033
	(0.6574)∗∗∗	(0.6149)∗∗∗	(0.6101)∗∗∗
	[0.6740]∗∗∗	[0.6274]∗∗∗	[0.6227]∗∗∗
	{0.7871}∗∗∗	{0.6658}∗∗∗	{0.6648}∗∗∗
log(Maturity of relationship)^2	−0.3805	−0.1954	−0.1950
	(0.0955)∗∗∗	(0.0869)∗∗	(0.0858)∗∗
	[0.0972]∗∗∗	[0.0882]∗∗	[0.0871]∗∗
	{0.1160}∗∗∗	{0.0975}∗∗	{0.0970}∗∗
log(Distance)	−1.1565	−0.5794	−0.5748
	(0.1349)∗∗∗	(0.0993)∗∗∗	(0.0983)∗∗∗
	[0.1347]∗∗∗	[0.0999]∗∗∗	[0.0988]∗∗∗
	{0.1470}∗∗∗	{0.1018}∗∗∗	{0.1003}∗∗∗
	Identity-based distance		
Different gender	−1.2549	−1.2042	−1.2130
	(0.2375)∗∗∗	(0.2397)∗∗∗	(0.2379)∗∗∗
	[0.2322]∗∗∗	[0.2370]∗∗∗	[0.2347]∗∗∗
	{0.1570}∗∗∗	{0.1781}∗∗∗	{0.1820}∗∗∗
Different education	−0.5378	−0.2830	−0.2833
	(0.1406)∗∗∗	(0.0924)∗∗∗	(0.0927)∗∗∗
	[0.1411]∗∗∗	[0.0923]∗∗∗	[0.0927]∗∗∗
	{0.1555}∗∗∗	{0.1062}∗∗∗	{0.1066}∗∗∗
log(Difference in age of managers)	−0.0695	−0.0792	−0.0793
	(0.0244)∗∗∗	(0.0214)∗∗∗	(0.0215)∗∗∗
	[0.0244]∗∗∗	[0.0216]∗∗∗	[0.0217]∗∗∗
	{0.0252}∗∗∗	{0.0224}∗∗∗	{0.0226}∗∗∗
log(Diff. in exp. on the line)	−0.3090	−0.3545	−0.3533
	(0.1057)∗∗∗	(0.0916)∗∗∗	(0.0918)∗∗∗
	[0.1044]∗∗∗	[0.0909]∗∗∗	[0.0912]∗∗∗
	{0.0986}∗∗∗	{0.0828}∗∗∗	{0.0838}∗∗∗
Observations	28492	28492	28492
Mean of Y	.113	.113	.113
SD	.498	.498	.498
Effect when X1= 1%	2.88 %	2.96 %	2.77 %
Effect when X1= 5%	15.28 %	15.71 %	14.61 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of above-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of these workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of above-median efficiency workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

[93]We add ln(Maturity)^2 to better see the nuance in the effect of maturity between high- and low-quality workers.

[94]In Tables H3 and H4, we present the same regressions where we use overall differences in absenteeism on the RHS as in Table 2 instead of the difference in absenteeism of low-efficiency (high-efficiency) workers as in Table H1 (H2).

We find that the difference in absenteeism of low-efficiency workers, maturity, gender, and differences in experience have a similar significant effect as we found in the pooled regression of Table 2. However, other demographics as well as physical distance have no statistical impact on this number, though the point estimates remain negative. On the other hand, the difference in absenteeism in higher-efficiency workers have a smaller effect on the number of high-efficiency workers borrowed compared to the pooled regression, but the point estimates are all larger in magnitude for the rest of the coefficients. This latter feature suggests that physical distance and demographics differences between managers are more important when it comes to trading more valuable workers. In particular, the effect of maturity is always larger for high-quality workers given the support of the data than it is for low-quality workers indicating that trust is particularly important for better workers.

Tables H3 and H4 are analogous to Tables H1 and H2, however the absenteeism variable represents the difference in *total* absenteeism. That is, the difference in absenteeism of workers with efficiency below *and* above the median as in Table 2.

Table H3: Lower efficiency workers

	Nb. Below Med. eff.		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	6.1154	6.0691	5.8423
	(1.9200)∗∗∗	(1.8500)∗∗∗	(1.7895)∗∗∗
	[1.9497]∗∗∗	[1.8761]∗∗∗	[1.8166]∗∗∗
	{2.6839}∗∗	{2.3909}∗∗	{2.3936}∗∗
log(Maturity of relationship)	2.3787	1.9644	1.9479
	(0.5128)∗∗∗	(0.4841)∗∗∗	(0.4785)∗∗∗
	[0.5244]∗∗∗	[0.4840]∗∗∗	[0.4784]∗∗∗
	{0.6381}∗∗∗	{0.5768}∗∗∗	{0.5692}∗∗∗
log(Maturity of relationship)^2	−0.2804	−0.0813	−0.0786
	(0.0761)∗∗∗	(0.0690)	(0.0681)
	[0.0778]∗∗∗	[0.0689]	[0.0681]
	{0.0981}∗∗∗	{0.0837}	{0.0826}
log(Distance)	−0.6605	−0.0564	−0.0557
	(0.1387)∗∗∗	(0.1247)	(0.1245)
	[0.1398]∗∗∗	[0.1255]	[0.1252]
	{0.1560}∗∗∗	{0.1378}	{0.1373}
	Identity-based distance		
Different gender	−0.8819	−0.9076	−0.9096
	(0.4069)∗∗	(0.3642)∗∗	(0.3659)∗∗
	[0.4057]∗∗	[0.3656]∗∗	[0.3674]∗∗
	{0.4165}∗∗	{0.4240}∗∗	{0.4259}∗∗
Different education	−0.3743	−0.0441	−0.0441
	(0.1667)∗∗	(0.1368)	(0.1369)
	[0.1666]∗∗	[0.1368]	[0.1369]
	{0.1743}∗∗	{0.1433}	{0.1433}
log(Difference in age of managers)	−0.0188	−0.0289	−0.0288
	(0.0239)	(0.0215)	(0.0215)
	[0.0237]	[0.0210]	[0.0210]
	{0.0249}	{0.0209}	{0.0209}
log(Diff. in exp. on the line)	−0.2437	−0.2731	−0.2731
	(0.1192)∗∗	(0.1154)∗∗	(0.1153)∗∗
	[0.1177]∗∗	[0.1141]∗∗	[0.1140]∗∗
	{0.1110}∗∗	{0.1049}∗∗∗	{0.1048}∗∗∗
Observations	27560	27560	27560
Mean of Y	.099	.099	.099
SD	.468	.468	.468
Effect when X1= 1%	6.31 %	6.26 %	6.02 %
Effect when X1= 5%	35.77 %	35.45 %	33.93 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of below-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of all workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of all workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

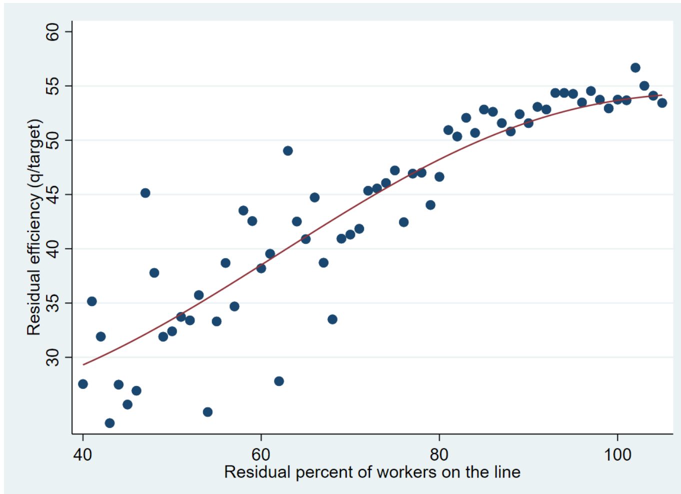
Table H4: Higher-efficiency workers

	Nb. above Med. eff.		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	5.1468	4.4450	3.9507
	(2.1755)$**$	(2.0689)$**$	(1.9814)$**$
	[2.1579]$**$	[2.0665]$**$	[1.9847]$**$
	{2.4515}$**$	{2.1238}$**$	{2.0116}$**$
log(Maturity of relationship)	2.7917	2.4619	2.4633
	(0.6430)$***$	(0.6349)$***$	(0.6271)$***$
	[0.6650]$***$	[0.6500]$***$	[0.6425]$***$
	{0.7922}$***$	{0.6900}$***$	{0.6874}$***$
log(Maturity of relationship)^2	-0.3465	-0.1769	-0.1760
	(0.0926)$***$	(0.0893)$**$	(0.0878)$**$
	[0.0949]$***$	[0.0911]$*$	[0.0897]$**$
	{0.1162}$***$	{0.1006}$*$	{0.0999}$*$
log(Distance)	-1.1661	-0.5901	-0.5879
	(0.1386)$***$	(0.1031)$***$	(0.1022)$***$
	[0.1383]$***$	[0.1038]$***$	[0.1028]$***$
	{0.1426}$***$	{0.0934}$***$	{0.0927}$***$
	Identity-based distance		
Different gender	-1.2616	-1.2157	-1.2229
	(0.2068)$***$	(0.2133)$***$	(0.2116)$***$
	[0.2016]$***$	[0.2061]$***$	[0.2047]$***$
	{0.1522}$***$	{0.1810}$***$	{0.1851}$***$
Different education	-0.5918	-0.3451	-0.3452
	(0.1417)$***$	(0.0980)$***$	(0.0978)$***$
	[0.1440]$***$	[0.0996]$***$	[0.0997]$***$
	{0.1363}$***$	{0.0886}$***$	{0.0885}$***$
log(Difference in age of managers)	-0.0763	-0.0866	-0.0869
	(0.0263)$***$	(0.0222)$***$	(0.0224)$***$
	[0.0261]$***$	[0.0220]$***$	[0.0222]$***$
	{0.0300}$**$	{0.0244}$***$	{0.0247}$***$
log(Diff. in exp. on the line)	-0.2602	-0.3237	-0.3232
	(0.1019)$**$	(0.0922)$***$	(0.0923)$***$
	[0.1009]$***$	[0.0905]$***$	[0.0905]$***$
	{0.1003}$***$	{0.1008}$***$	{0.1004}$***$
Observations	27560	27560	27560
Mean of Y	.116	.116	.116
SD	.511	.511	.511
Effect when X1= 1%	5.28 %	4.55 %	4.03 %
Effect when X1= 5%	29.35 %	24.89 %	21.84 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of above-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of all workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of all workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

I Additional analyses for the simulations

Figure I1: Reduced-form production function



Note: We compute the average residual efficiency of the workers on the line and the average residual percentage of workers on the line (in 1% bins), excluding observations from lines in the first week of an order. We obtain the residualized variables by removing line, year, month, and day of the week fixed effects. We then fit a five-degree polynomial by OLS restricting the polynomial to be positive on the support of the data and ensuring that more workers on the line never diminishes efficiency. We do the polynomial fit in Matlab using the Linear Least Squares command (lsqlin) which allows us to impose that the first derivative of the polynomial is non-negative on the support. The resulting polynomial is given by : $y = 24.5860 + 0.0458x - 0.0070x^2 + 0.00036x^3 + (-3.8513 \times 10^{-6})x^4 + (1.2463 \times 10^{-8})x^5$.

Table I1: Empirical tests with a binary variable for any demographic difference

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	5.7823	5.2853	4.9258
	(2.0215)∗∗∗	(1.7566)∗∗∗	(1.6720)∗∗∗
	[2.0364]∗∗∗	[1.7719]∗∗∗	[1.6945]∗∗∗
	{2.5917}∗∗	{2.0397}∗∗∗	{1.9709}∗∗
log(Maturity of relationship)	0.3783	1.3090	1.3134
	(0.1157)∗∗∗	(0.0845)∗∗∗	(0.0840)∗∗∗
	[0.1170]∗∗∗	[0.0848]∗∗∗	[0.0843]∗∗∗
	{0.1349}∗∗∗	{0.0892}∗∗∗	{0.0888}∗∗∗
log(Distance)	−0.8466	−0.3267	−0.3267
	(0.1223)∗∗∗	(0.0922)∗∗∗	(0.0922)∗∗∗
	[0.1232]∗∗∗	[0.0934]∗∗∗	[0.0935]∗∗∗
	{0.1618}∗∗∗	{0.1248}∗∗∗	{0.1251}∗∗∗
Demographic distance	−0.4473	−0.3219	−0.3195
	(0.1817)∗∗	(0.1576)∗∗	(0.1578)∗∗
	[0.1837]∗∗	[0.1602]∗∗	[0.1602]∗∗
	{0.1872}∗∗	{0.2046}	{0.2051}
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	5.95 %	5.43 %	5.05 %
Effect when X1= 5%	33.52 %	30.25 %	27.93 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers have any demographic differences. More precisely, this variable equals 1 when managers are of different genders, or have a different level of education, or their age difference is above median, or their experience difference is above median. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table I2: Empirical tests with a binary variable for whether the partner is a main partner

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\,i - \%Abs\,j)/2$	5.7783	5.2232	4.8372
	(2.0030)∗∗∗	(1.7450)∗∗∗	(1.6579)∗∗∗
	[2.0039]∗∗∗	[1.7576]∗∗∗	[1.6777]∗∗∗
	{2.5540}∗∗	{1.9998}∗∗∗	{1.9313}∗∗
log(Maturity of relationship)	0.2441	1.2077	1.2116
	(0.1022)∗∗	(0.0893)∗∗∗	(0.0887)∗∗∗
	[0.1031]∗∗	[0.0899]∗∗∗	[0.0893]∗∗∗
	{0.1165}∗∗	{0.0937}∗∗∗	{0.0939}∗∗∗
log(Distance)	−0.5467	−0.1532	−0.1529
	(0.0961)∗∗∗	(0.0832)∗	(0.0830)∗
	[0.0975]∗∗∗	[0.0847]∗	[0.0845]∗
	{0.1027}∗∗∗	{0.0995}	{0.0990}
Main partner	0.9719	0.4123	0.4121
	(0.1556)∗∗∗	(0.1208)∗∗∗	(0.1208)∗∗∗
	[0.1550]∗∗∗	[0.1197]∗∗∗	[0.1198]∗∗∗
	{0.1905}∗∗∗	{0.1349}∗∗∗	{0.1356}∗∗∗
	Identity-based distance		
Different gender	−0.7073	−0.9035	−0.9075
	(0.1721)∗∗∗	(0.1814)∗∗∗	(0.1834)∗∗∗
	[0.1603]∗∗∗	[0.1755]∗∗∗	[0.1780]∗∗∗
	{0.3049}∗∗	{0.3400}∗∗∗	{0.3425}∗∗∗
Different education	−0.3885	−0.1559	−0.1560
	(0.1047)∗∗∗	(0.0868)∗	(0.0866)∗
	[0.1069]∗∗∗	[0.0880]∗	[0.0879]∗
	{0.1183}∗∗∗	{0.0895}∗	{0.0891}∗
log(Difference in age of managers)	−0.0320	−0.0506	−0.0506
	(0.0187)∗	(0.0160)∗∗∗	(0.0160)∗∗∗
	[0.0186]∗	[0.0159]∗∗∗	[0.0159]∗∗∗
	{0.0208}	{0.0172}∗∗∗	{0.0174}∗∗∗
log(Diff. in exp. on the line)	−0.2310	−0.2866	−0.2870
	(0.0898)∗∗	(0.0775)∗∗∗	(0.0772)∗∗∗
	[0.0892]∗∗∗	[0.0764]∗∗∗	[0.0761]∗∗∗
	{0.0778}∗∗∗	{0.0777}∗∗∗	{0.0774}∗∗∗
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	5.95 %	5.36 %	4.96 %
Effect when X1= 5%	33.5 %	29.84 %	27.36 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level for main partners on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each manager as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

J Home line

For all units in the data, we take the longest time period for which we have recorded productivity data which is approximately 1 year. This way, the definition of home lines is not affected by the period we keep to construct the dyadic dataset. To define the workers' home line, we proceed as follows:

1. We break this period into trimesters and find on which line do workers spend the most days for each of those 3 months periods and take that line as the first approximation of their home line.

2. Then, we investigate whether a worker's home line changes across two trimesters. When it is the case, we look at which line this worker was working on around the trimester cutoff. If a worker is on their new home line a few days before the trimester cutoff, we update that worker's home line for those days to be the home line of the upcoming trimester rather than the home line of the current trimester (see Table J1). We do a similar updating when a worker is working on their home line of the previous trimester a few days in the current trimester where their home line changes (see Table J2). We carefully take into account days traded and days absent in this exercise.

Table J1: First adjustment

	Trimester 1					Trimester 2				
Day of the trimester	n-4	n-3	n-2	n-1	n	1	2	3	4	5
Home line	1	1	1	1	1	2	2	2	2	2
Line where the worker is assigned	1	1	2	2	2	2	2	2	2	2
Updated home line	1	1	2	2	2	2	2	2	2	2

Table J2: Second adjustment

	Trimester 1					Trimester 2				
Day of the trimester	n-4	n-3	n-2	n-1	n	1	2	3	4	5
Home line	1	1	1	1	1	2	2	2	2	2
Line where the worker is assigned	1	1	1	1	1	1	1	1	2	2
Updated home line	1	1	1	1	1	1	1	1	2	2

3. With this updated definition of home line for the workers, we find whether they spent more than or equal to 40% of the days they were present during a given trimester in a near consecutive way on a different line than their home line currently defined. When this is the case and the worker worked more than 20 days during this trimester, we update their home line for those consecutive days to be the line where they spent those days. When doing this exercise, we account for trades and days absent. Consider a case where a worker is present 80 days in a 3-month period. They spend 45 days on line 1. Therefore, line 1 is currently their home line given our definition. They spend 32 (40%) near consecutive days on line 2, but they are seen on line 3 three days in that period. Even if the 32 days were not consecutive, they were clearly assigned to line 2 over that period and was traded 3 days to line 3. Therefore, we update their home line over that period to be line 2 (see Table J3). A similar adjustment is done if the worker is absent (see table J4 where *a* indicates that the worker is absent). We, then, redo step 2 in case the adjustments done in step 3 were right at the cutoff of 2 trimesters.

Table J3: Third adjustment

	Trimester 1														
Day of the trimester	1	2	3	4	5	6	7	8	...	32	33	34	35	...	80
Home line	1	1	1	1	1	1	1	1	...	1	1	1	1	...	1
Line where the worker is assigned	3	2	2	3	3	2	2	2	...	2	1	1	1	...	1
Updated home line	2	2	2	2	2	2	2	2	...	2	1	1	1	...	1

Table J4: Fourth adjustment

	Trimester 1														
Day of the trimester	1	2	3	4	5	6	7	8	...	32	33	34	35	...	80
Home line	1	1	1	1	1	1	1	1	...	1	1	1	1	...	1
Line where the worker is assigned	a	2	2	a	a	2	2	2	...	2	1	1	1	...	1
Updated home line	2	2	2	2	2	2	2	2	...	2	1	1	1	...	1