Absenteeism, Productivity, and Relational Contracts Inside the Firm*

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Abstract

We leverage a unique dataset that tracks transfers between managers in Indian ready-made garment factories to study how managers cope with worker absenteeism on their teams. We document that worker absenteeism shocks are frequent, often large, weakly correlated across managers, and have substantial negative impacts on team productivity, implying gains from sharing workers. Managers respond to shocks by lending and borrowing workers in a manner consistent with relational contracting. But many potentially beneficial transfers are unrealized, because managers' primary relationships are with a very small subset of potential partners. Counterfactual simulations reveal large gains to forming additional relationships among managers.

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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 this knowledge gap. We shed light on 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., 2019a,c; 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., 2019b).

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 one 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 "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. 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.[1] 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.

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 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 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 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.

To further study the nature of lending and borrowing behavior among managers, we present a simple model of relational contracting, in which two managers decide whether and how much to trade with each other. The model, which features stochastic absenteeism states, fixed costs of trading, and learning about partners' (privately known) types, generates a unique symmetric stationary relational contract that characterizes managers' interactions. Additional predictions can be made for interactions along the transition to this steady state, as managers learn about each other's type.

We test the model's 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. In line with the model's predictions, 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

[1] Managers in this setting are also able to identify "unobservable" comparative advantages in particular tasks for their own team's workers (Adhvaryu et al., 2019b); these differences among otherwise similar workers are not readily evident to other managers, which compounds the asymmetric information problem just described.

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.[2]

Finally, 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 0.9 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. We trace out a concave function that shows that productivity would increase substantially (by up to 1.6 percent) if the costs of relationship formation decreased. That is, the value of additional relationships to the firm in this context is quite substantial. Such an increase in efficiency would translate roughly to a 1.44 million US dollars increase in annual profit for the firm. Benchmarking these gains to the (simulated) gains from a reduction in absenteeism, we find that maximizing the number of relationships would achieve up to 98% of the productivity gained from a 50% reduction in absenteeism, suggesting that the costs of misallocation of labor *within* the firm can be as important as the costs of market failures (such as those that lead to worker absenteeism) outside the firm's direct control.

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 relatively scant. We provide direct empirical characterization of relational contracts *within* the firm. 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 co-workers 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., 2019c; Frederiksen et al., 2017; Hoffman and Tadelis, 2018; Lazear 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

[2]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 the model of relational contracts set out in the paper.

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.[3]

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., 2019a,b; 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.

The rest of the paper is organized as follows. Section 2 describes the empirical context. Section 3 introduces the data and presents some empirical facts consistent with relational contracting among managers. Section 4 presents the model and resulting predictions. Section 5 describes the empirical strategy for testing the model's predictions and presents results. Section 6 compares the results of simulations depicting, alternately, varying intensity of relational contracting among managers and reduced absenteeism. Finally, section 7 concludes.

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 in the world.[4] 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, Mens, and Ladies) to factories based on capacity and regulatory and/or compliance clearance (i.e., whether a particular factory 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.[5] The order will then be produced in its entirety by that production line, and then be prepared for

[3]Middle managers like the production line supervisors we study are often emphasized as enablers or constrainers of worker productivity (Adhvaryu et al., 2019c; 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).

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

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

shipment in advance of the contracted delivery date.

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 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.[6]

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 line.

[6] 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). 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.

2.3 The role of managers

Each production line has a manager (and sometimes several assistant managers, often serving also 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 his line and is 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 workers across machines, or add a helper or second machine to some critical operations, preserving the line architecture otherwise (Adhvaryu et al., 2019b). 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., 2019c).

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 her 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). There are few consequences for workers of taking unauthorized leave beyond lost wages; workers are almost never fired given that Indian labor law mandates very high firing costs, particularly for large firms (Adhvaryu et al., 2013).

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 operates 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 additional workers, are best assessed by the line manager himself, as he is most knowledgeable of the style of garment currently being produced and the (idiosyncratic) capabilities of the remaining set of available workers on his line. It is infeasible given time and information constraints that managers are able to accurately assess manpower needs of lines other than their own.[7] 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.[8]

2.5 Cooperation between managers

In practice, in particular when facing larger absenteeism shocks than 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 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 recalibration 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 the primary safeguard against the deleterious effects of absenteeism on productivity.

3 Data and Empirical Facts

To investigate this claim further, 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 data shows that

[7]Managers in this setting are also able to identify "unobservable" comparative advantages in particular tasks for their own team's workers (Adhvaryu et al., 2019b). These differences among otherwise similar workers are not readily evident to other managers.

[8]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. Given this, they need to decide whether they should try to borrow workers from other lines.

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.[9]

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. 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 $5/50 = 10\%$.[10] Accordingly, 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 know that the manager of that line has borrowed them from their home line manager for the day.[11]

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.[12] 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.[13]

[9]We provide more detail on the determination of workers' home line in Appendix E.

[10]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.

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

[12]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.

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

Distance is measured in feet between two production lines on the same floor.[14]

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 1, 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. Most managers are male and Kannada-speaking. 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 Bengaluru metro area.

Table 1: 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 metro area.

In Table 2, 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 21-22 lines (mean 21.5, SD 2.65) spread across 3-4 floors (mean 3.55, SD 1.71) with roughly 6-7 lines on each floor (mean 6.63, SD 2.74). Lines are on average 9 to 10 feet from their potential partners on the factory floor.

In Figure 1, we show the frequency of trades of the workers in our sample. Over the span of the data, approximately half of the workers are traded to other lines, and a large fraction of them are traded multiple times.

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

Table 2: Summary statistics at the line level

Variables	Mean/(S.D.)
Number of home-line workers (absent or not)	56.27 (16.49)
Number of workers present on the line (home-line 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 possibly 1 to 2 assistant managers, often serving also 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.

Figure 1: 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.

3.2 Absenteeism and line productivity

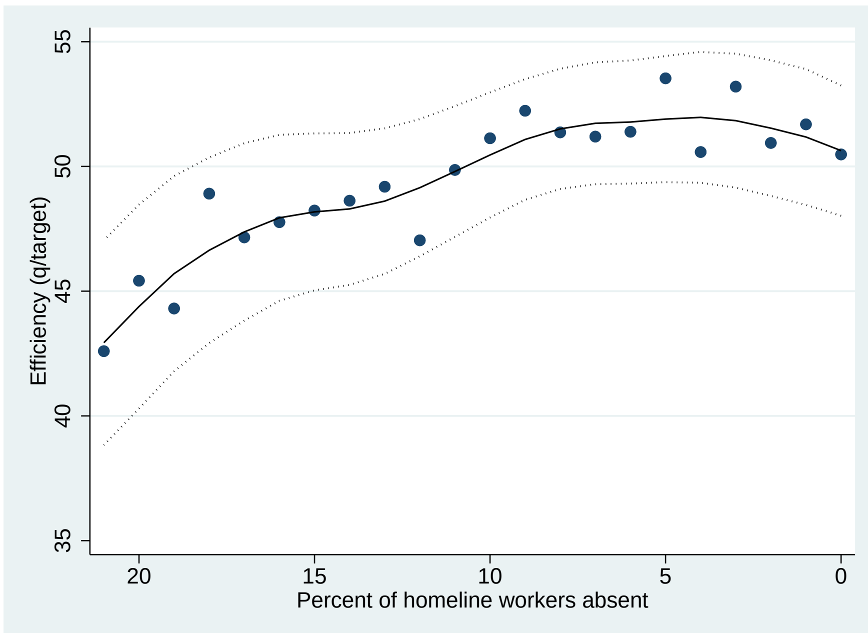
We begin our presentation of empirical facts by documenting the relationship between absenteeism and productivity. In the garment industry, efficiency is the global standard to measure productivity. The target quantity of a specific garment to be produced is determined from a measure of garment complexity called the standard allowable minute, or SAM. SAM is the number of minutes it should take, in an optimal setting, to produce one unit of a certain style of garment (e.g., one men's shirt).[15]

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

[15]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 than what the SAM measure would suggest.

with SAM of .5 should complete $60/0.5 = 120$ operations per hour.[16] The efficiency of a worker (per hour) is simply the number of operations she is 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 her efficiency is 50% for that day.

Figure 2: Average efficiency on the line by "home line" workers absent



Note: We compute the average efficiency of the workers on the line by percentages of absenteeism. The scatter depicts the mean within integer bins of absenteeism; the solid line depicts a nonparametric fit; and the dotted lines represent the 95% confidence interval. To compute this picture, we restrict focus in this graph to days in which lines have 25% absenteeism or less as larger absenteeism is rarer and less likely to reflect the idiosyncratic absenteeism we are modeling here.

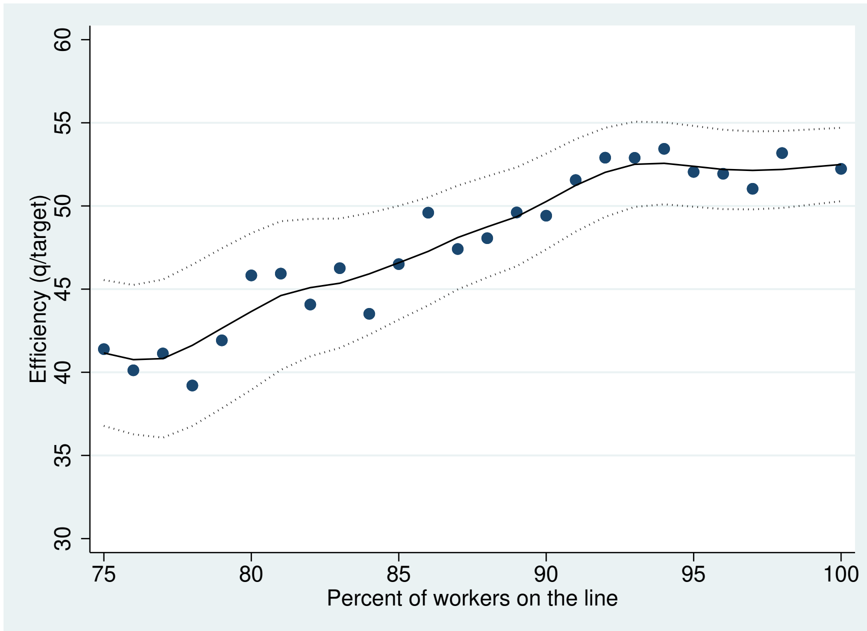
To calculate daily efficiency of a line, we simply average the efficiency of the workers working on this line that day. In our data, we estimate that the average hourly efficiency at the line level is 49.09% (SD 15.85%). Realized efficiency is far from 100% because the SAM reflects production in an optimal 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 2 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

[16]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.

less than 10% absenteeism to below 45% at 20% absenteeism.

Figure 3: Average efficiency by percentage of workers present on the line



Note: We plot the average efficiency of the line against the percentage of workers working on the line. The percentage of workers on the line is calculated relative to the number of home line workers assigned to this line. Note this percentage can exceed 100. If a line has 55 home line workers assigned to it, but 57 workers are working on the line on a given day, the percentage of workers on the line is then 57/55=104% that day. These cases are rare and not included in the picture. For the same reason, we do not show cases where less than 75% of the workers are working on the line. The scatter depict the mean within integer bins of absenteeism; the solid line depicts a nonparametric fit; and the dotted lines represent the 95% confidence interval.

Figure 3, on the other hand, plots the average efficiency of the line against the number of workers present on the line that day (whether or not this line is their home line) as a percentage of the number of home line workers assigned to this line. 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%.

Taken together, Figures 2 and 3 show that large absenteeism shocks appear to be detrimental to line productivity, but that fairly small shocks have little impact. Accordingly, a 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 count the percentage of lines in the sample that experience an absenteeism of at least 10% for each day of production and we plot the density across days. We do the same for shocks of at least 15%, 20%, and 25% and plot each density in Figure 4. The figure clearly shows that large shocks are quite frequent. 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).

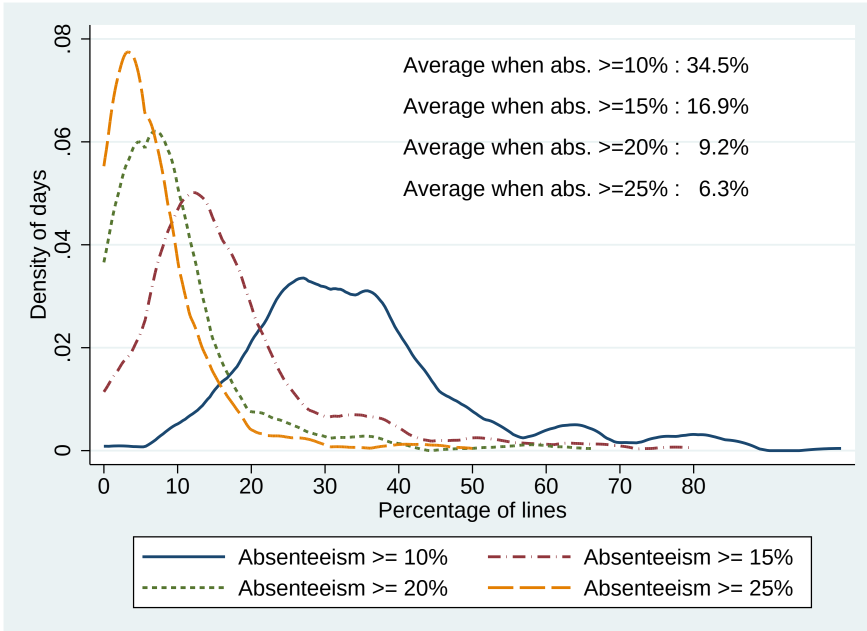
In Table 3, we report the average within day correlation in absenteeism of different lines across units (column 1), within units (column 2), and within floors (column 3). While the correlation increases slightly across columns, the magnitudes all remain small. The within floor-day correlation (column 3), 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.

Table 3: 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 lines in all units 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.

Figure 4: Frequency of large absenteeism shocks



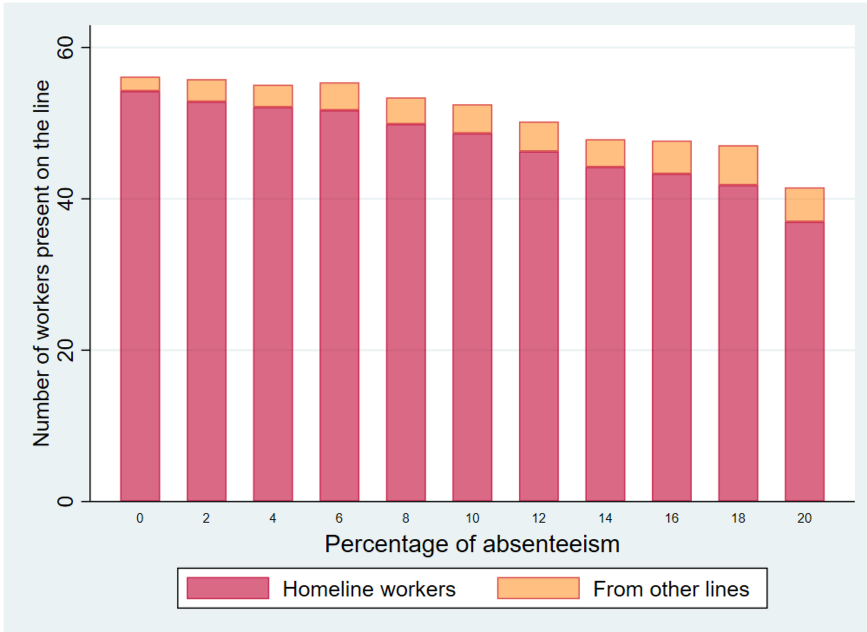
Note: We calculate the percentage of lines with an absenteeism level of at least 10%, 15%, 20%, and 25% on a given day. We take the average number of lines which such shock across days and plot the distribution. We report the average number of lines with at least a 10%, 15%, 20%, and 25% absenteeism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

3.4 Managers borrow workers to mitigate the impact of absenteeism

Figures 2 and 3 indicate that managers should want to borrow more workers as their absenteeism increases, and Table 3 suggests that some other lines on the floor should likely be in the position that day to spare some workers. Indeed, Figure 5 shows the number of workers borrowed by a line grows with that line's percentage of absenteeism. Due to the shape of the relationship in Figure 3, one would expect that mangers 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.

However, Figure 6, which zooms in on the number of workers borrowed for each level of absenteeism, shows that the relationship between the number of workers borrowed and absenteeism is increasing, but concave. 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.

Figure 5: The number of workers borrowed increases with absenteeism

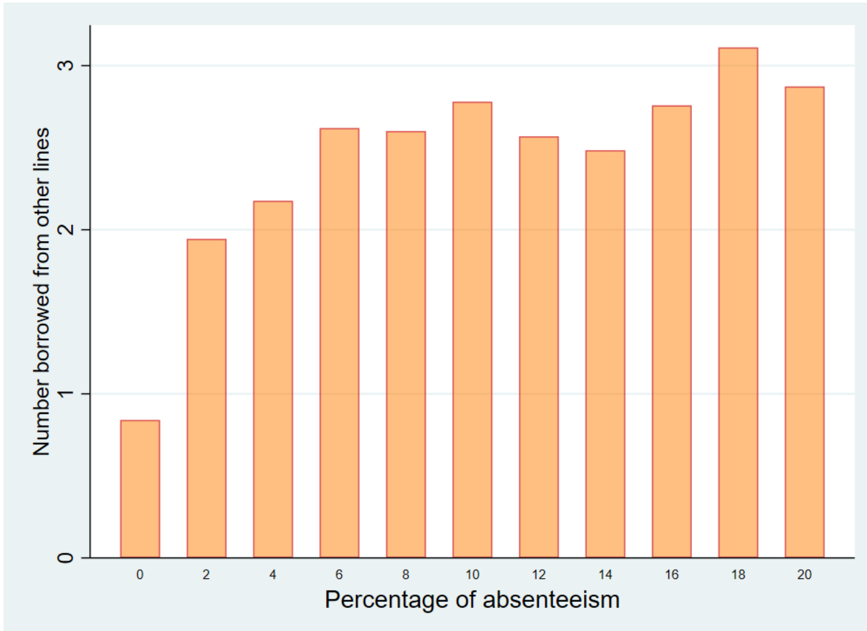


Note: The full bars represent the average number of workers on the line for different percentages of absenteeism across the lines in our sample. The darker bars indicate the average number of home line workers on the line and the paler bars represent average number of workers borrowed.

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 1 or 2 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 so as to fall below 93% (as depicted in Figure 3).

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. However, as we show below, line managers actively trade with only a few other managers, consistent with partnerships being costly to establish and maintain.

Figure 6: The number of workers borrowed increases up to a certain point



Note: In this graph, 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 Figure 5.

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. We regress 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. Table 4 shows 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. We find that a 10% increase in absenteeism decreases efficiency by roughly 4%. In Appendix C, we show that these findings are robust (and indeed statistically equivalent) when using an instrumental variable (2SLS) analysis. We also check that the incidence of absenteeism shocks is balanced across lines and managers of varying productivities.

Table 4: Productivity losses from absenteeism

	Efficiency (q/target)		
	(1)	(2)	(3)
Percentage of Absenteeism	-0.3971	-0.4068	-0.4451
	$(0.0374)***$	$(0.0307)***$	$(0.0317)***$
	$[0.0381]***$	$[0.0311]***$	$[0.0321]***$
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 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.

3.6 Many potential trading partnerships are left unrealized

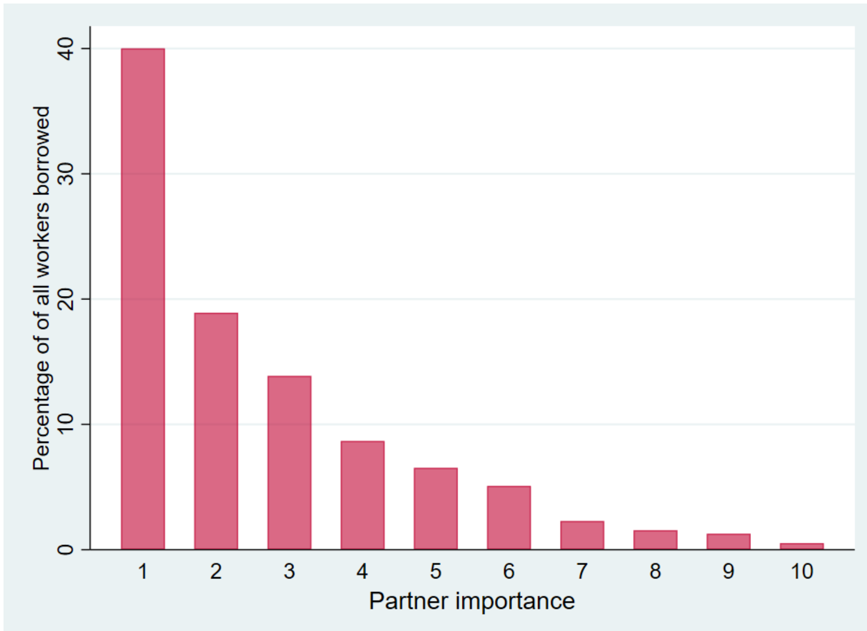
The previous section indicates that although managers exchange workers to cope with absenteeism, the trades are not sufficient to completely mitigate the impacts of absenteeism on productivity. We next document that managers seem to forego many potential partnerships. If we rank a manager's partners 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 over the span of the data. If we assume 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.

Figure 7 plots the average percentage of all workers borrowed across managers by the importance of its partners. For each manager, we compute the frequency of trade for each partner. The most important partner (rank 1) is the partner a manager trades with the most often. The intensity of trade is not uniform across partners. Indeed, on average, 40% of all workers borrowed come from a single partner. 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.

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. For example, managers conduct nearly 66% of their trading with managers with a similar level of education and 71% of their trades with managers of the same gender.[17]

Figure 7: Percentage of all workers borrowed by the importance of partners



Note: We calculate the frequency of trades between each manager (number of workers traded × 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 over the span of the data that comes from each of these partners.

4 Theory and Empirical Predictions

In this section, we posit a simple model of managers' interactions and generate empirical predictions which we test in the subsequent section. The model is designed to match the qualitative features of the context described above. We assume that managers of production lines have private information about their types (reliable or unreliable) and the number of home line workers present on a given day. Managers can borrow or lend workers from their main partners depending on the number of home line workers present on their and partners' lines, but there is no contract enforcement (Levin, 2003; MacLeod and Malcomson, 1989). Transaction costs affect the intensive and the extensive margin of the number of workers borrowed/lent. Finally, beliefs about main partners' types are updated following Bayes' rule.[18]

[17]From the data, we can tell whether the managers (1) didn't passed the 10th grade, (2) passed the 10th grade, (3) completed high school (passed the 12th grade), or (4), have a bachelor or higher degree. Managers have a similar level of education if they fall in the same category or are 1 category apart.

[18]Note that here we study a typical pair of managers and how they borrow/lend workers depending on different levels of absenteeism. We ignore how partnerships are formed (i.e., we assume that managers are matched randomly),

We first turn to the analysis of the model with symmetric managers (i.e., 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. Next, we analyze the transition path to a stationary contract of the model with uncertainty over managerial type. On a convergence path, the incentive compatibility constraint suggests a positive relationship between the number of workers borrowed/lent and the maturity of the relationship.[19]

4.1 Setup

We study a set of homogeneous managers (production lines), $\mathcal{K}$, that 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, $\bar{y}$, but 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 $y_{i,t} \in \{y_1, y_2, \cdots, y_n\}$ and $y_1 < y_2 < \cdots < y_n$ with $y_n \equiv \bar{y}$.

Each production line produces $f(y_{i,t} - \theta_{ij,t})$ 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 $y_{i,t} - \theta_{ij,t} > 0$.[20]

We assume that $y_{i,t}$ is privately known by the manager of production line i and follows a discrete distribution, $\pi_i(\cdot)$, independent across time and of the state of their peers, $y_{-i,t}$ and $\pi_{-i}(\cdot)$. We assume that distribution functions are symmetric such that $\pi_i(\cdot) = \pi(\cdot)$ for every line $i \in \mathcal{K}$. In particular from these 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 $j \in \mathcal{K}$ 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 γ_0, and the measure of unreliable managers is $1 - \gamma_0$. Managers privately know their own type and have a prior about their partner's type γ_0 that is updated every period.[21] Reliable managers always tell the truth about the current number of home line workers that they have. Unreliable managers lie with probability $1 - \rho$ about their current number of home line workers, whenever their state is better than their partner's state. This probability is known to both parties and constant over time.

In each period, managers are matched randomly and establish (or continue) bilateral relationships. In a potentially ongoing relationship, manager i agrees to help manager j if i is in a (reported) better state (i.e., higher proportion of home line workers present) than j; in return, j agrees to help

and we shut down experimentation.

[19]Note that the *standard* relational contract model assumes quasi-linear utility and monetary transfers that can substitute for variation in continuation payoffs (Levin, 2003). In our model agents are risk-averse, thus our model hews a bit closer to risk-sharing and informal insurance models (Coate and Ravallion, 1993).

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

[21]Belief updating is explained in detail in Section 4.3.

i when their states are reversed in the future. At the beginning of the period, the number of home line workers that manager i has is unknown to manager j, and vice versa. At the end of the period managers confirm if their partner told the truth, then, a match can be dissolved endogenously if either party in the current relational contract decides to leave the match.[22]

Finally, we assume that there is a transaction cost, $c_{ij} \geq 0$, which is ij-specific and constant across states.[23] Transaction costs affect the intensive margin (i.e., the number of workers borrowed or lent) but can also affect the extensive margin if they are large enough (i.e., the frequency of transfers between i and j).

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).

4.2 Timing

At the beginning of the period, nature selects the states of each production line, that is, $Y(t) = (y_{i,t}, y_{j,t})$ for $i, j \in \mathcal{K}$, and U-type managers know if they will tell the truth or not. After observing the history of the game, managers meet and declare their state. 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 his 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_{ij}, is high (compared to i's state), i does not transfer any of his 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, he does not tell the truth about his state with probability $1 - \rho$, then, i does not transfer any of his home line workers to manager j and manager j ends the relationship at the end of the period. If i tells the truth, the outcome can be (1) or (2).[24]

Finally, managers update their beliefs about their partner's type, period t ends and period $t + 1$ begins.

4.3 Strategies, belief updating, and incentive constraints

As the solution concept we adopt symmetric perfect public equilibrium (SPPE). 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 his partner as a function of the (within-dyad) history of transfers. A relational contract consists of a strategy profile $\sigma = \left(\sigma^R, \sigma^U\right)$. Denote γ_t^{ij} as manager i's belief that his partner

[22]We can also assume that at the end of the period managers confirm if their partner told the truth with probability $\lambda \in (0, 1)$. The predictions of the model remain constant since unreliable managers every period lie with probability $1 - \rho$ about the current number of home line workers. For simplicity we assume that $\lambda = 1$.

[23]For example, the physical and demographic distances between i and j.

[24]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.

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

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

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 and truthfully reports his state, future payoffs from period t onward for a relationship are given by:

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

If i does not tell the truth and therefore does not lend j workers, future payoffs from t onward for a relationship are given by

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

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:

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

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

4.4 Symmetric Stationary Relational Contracts

To study a *symmetric stationary relational contract*, suppose first that $\gamma_0 = 1$, that is, all managers are reliable so that they do not need to update their beliefs.[25] The incentive compatibility constraint in this case is thus

$$f\left(y_i\right) - f\left(y_i - \theta_{ij}\right) + c_{ij} \leq \delta \left(U^R\left(\boldsymbol{\theta}\right) - V\left(n_i\right)\right). \tag{2}$$

Let α_{ij} be the value of y_i for which equation (4) 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

[25] 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^{ij}, converge to 1.

relational contract, $\boldsymbol{\theta}^*$, is such that it maximizes $U^R(\cdot)$ (see equation (D.1) in Appendix D) when restricting the domain to all symmetric non-negative allocations such that (2) 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 $\mathbb{R}^d$.[26]

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

$$\theta^*_{ij} = \min\left\{\hat{\theta}_{ij}, H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)\right\}, \tag{3}$$

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

$$\Delta\left(y_i, c_{ij}, H\left(y_i, c_{ij}, w\right)\right) \equiv f\left(y_i\right) - f\left(y_i - H(y_i, c_{ij}, w)\right) + c_{ij} - w = 0, \tag{4}$$

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 (4). Note that the optimal transfer is always less than or equal to the efficient transfer, $\hat{\theta}_{ij}$.

From (4), 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. Restricting our attention to this relevant case, in the predictions that follow, we assume that the first best allocation is never achieved.

4.5 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 (1), it follows that on the transition path to steady state, as the number of transfers increases, the present value of the relationship, $U^R_{i,t+1}\left(\boldsymbol{\theta}_{t+1}; \gamma^{ij}_{t+1}\right)$, 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

[26]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., $V \equiv V\left(n_i\right) = V\left(n_j\right)$.

for all $t \in \mathbb{N}$, $\theta^*_{ij,t} < \hat{\theta}_{ij}$.[27] From the proof of Proposition 2 in Appendix D, it is easy to show 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 $k \in \mathbb{N}$.[28]

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). Eventually, U-type managers will be found out, and those relationships will end.

4.6 Summary of Predictions

To summarize, the following are the five key predictions from this model that we take to the data. The first three predictions pertain to steady state comparative statics. 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...

- Prediction 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.
- Prediction 2: ...increases as the transaction cost between i and j decreases.

  Also, in a stationary relational contract:
- Prediction 3: As transaction costs decrease, the frequency of transfers between i and j increase.

The fourth and fifth prediction pertains to the transition path to the steady state. In particular, on the convergence path, as the maturity of the relationship (the cumulative number of transfers between managers i and j) increases

- Prediction 4: ...the amount borrowed by manager i from manager j also increases.
- Prediction 5: ... the frequency of transfers between i and j increase.

5 Empirical Tests of Model Predictions

In this section, we formally bring the predictions of the model to the data. The model yields predictions for how the number of workers borrowed by manager i from partner manager j should vary with the absenteeism on line i relative to absenteeism on line j, the maturity of the partnership

[27] 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 $\underline{\theta}$.

[28] Note that, in general, dynamic relational contracts are quasi-monotonic similar to Yang (2013).

with manager j, and the transaction cost.[29] In particular, the model predicts that manager i should borrow more workers from partner j as line i's absenteeism increases relatively to j''s and as the partnership ages. On the other hand, manager i should borrow less workers from partner j as the cost of the transaction between i and j rises.

5.1 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.[30] Our model predicts that this trade decision depends on the demographic similarity of the managers and the physical distance between the production lines (transaction cost). In that sense, our problem 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). Instead of countries trading goods, managers of different lines decide to borrow and lend workers to one another and thus, maintain a partnership. Accordingly, we follow this literature in estimating the following log-gravity equation:

$$\begin{aligned}\theta_{ijuft} = \alpha + \beta_1 \frac{(\%\,Abs_{iuft} - \%\,Abs_{juft})}{2} + \beta_2 ln(Maturity_{ijuft}) + \beta_3 ln(Dist_{ijuf}) + \beta_4 Gender_{ijuf} \\ + \beta_5 Education_{ijuf} + \beta_6 ln(Age_{ijuf}) + \beta_7 ln(Experience_{ijuf}) + \Phi + \varepsilon_{ijuft}, \end{aligned} \tag{5}$$

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. Our dependent variable, θ_{ijuft} the number of workers borrowed by manager i from manager j, both on floor f in factory unit u, on date t. Our main regressor is the average difference in absenteeism between manager i and its partner j at date t. Our model predicts that the number of workers borrowed is larger the worse is i's state compared to j's state.[31] We also include the natural log of the maturity of the relationship between the managers, the natural log of the distance between their line, and binary variables for whether the managers are of the same gender and have the same level of education as well as the natural log of the (absolute) difference in age and of the difference in experience of the managers in managing their current lines.[32] In certain specifications we account for learning-by-doing by including the natural log on the number of days since i's order started.[33]

[29] We use manager and production line interchangeably. Whenever we refer to manager i, we mean the manager of production line i.

[30] 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.

[31] 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 A, we show that the results hold if we include cases where j's absenteeism $> i$'s absenteeism.

[32] From the data, we can tell whether the managers (1) didn't passed the 10th grade, (2) passed the 10th grade, (3) completed high school (passed the 12th grade), or (4), have a bachelor or higher degree. Managers have a similar level of education if they fall in the same category.

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

The matrix Φ corresponds to different sets of cross-sectional and temporal fixed effects. In particular, we include include unit, manager i and manager j fixed effects as well as year, month and day of the week fixed effects to account for common seasonality in absenteeism across managers. 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. Second, we use a two-way clustering strategy with one cluster for the manager pair and one cluster for the date. 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.

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, we follow again the international trade literature and estimate the model using Poisson Pseudo Maximum Likelihood, or PPML (see, e.g., Bryan and Morten (2019)).

5.2 Results

Table 5 presents the results from the estimation of equation 5, 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%).[34] To Illustrate the size of the effect, consider a case where a manager has 1% absenteeism and borrows 1 worker from each of his 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 one more worker across the 3 partners, or 4 workers in total that day, if his absenteeism were to increase to 10.8-12.6%. If the managers absenteeism were to rise to 24.8-29.2%, he would borrow one additional worker from each of his 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.[35] Hence, a manger that borrows one worker in an average partnership would borrow one 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. All else equal, a manager borrows approximately 29% less from a manager that is 12 feet away compared to a manager 3 feet away.[36] 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.

equal to 0.

[34]The first coefficient is in decimals. The equation for the number of workers borrowed is $\theta^1_{ij} = e^{\beta_1 x_1 + X\beta}$. Consider a case where the main coefficient, x_1, increases by 1% (0.01), then $\theta^2_{ij} = e^{\beta_1 x_1 + \beta_1 0.01 + X\beta}$. Therefore, $\theta^2_{ij} - \theta^1_{ij} = (e^{\beta_1 0.01} - 1)\theta^1_{ij}$ and the percentage change in the number of workers borrowed is given by $100 \times \frac{\theta^2_{ij} - \theta^1_{ij}}{\theta^1_{ij}} = 100 \times (e^{\beta_1 0.01} - 1)$. 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%.

[35]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.

[36]The percentage change is $100 \times \frac{(e^{-0.246 \times ln(6)} - e^{-0.246 \times ln(3)})}{e^{-0.246 \times ln(3)}}$ = -28.93% in column 2 and -28.89% in column 3.

Table 5: Tests of model predictions

	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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. 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 managers 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.

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.[37] 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 1 year age difference.[38] 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 his junior or senior every 10 days. Similarly, managers tend to borrow more from partners with similar level of experience managing their current line. They tend to borrow 23-33% less from managers with 5 years difference 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.

On the whole, these results strongly suggest 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 mangers. Finally, the results suggest that both physical and identity-based, or demographic, distances impose substantial barriers on relationship formation and dynamics.

Table 6 reports the result of a logistic regression and shows how the previous 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 column 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% 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's is 6 feet away from i's 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.

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

[38] The percentage change is $100 \times \frac{(e^{-0.029 \times ln(10)} - e^{-0.029 \times ln(1)})}{e^{-0.029 \times ln(1)}}$ = -6.46% in column 1, and 11.9% in column 2 and 3.

Table 6: Tests of model predictions on the extensive margin

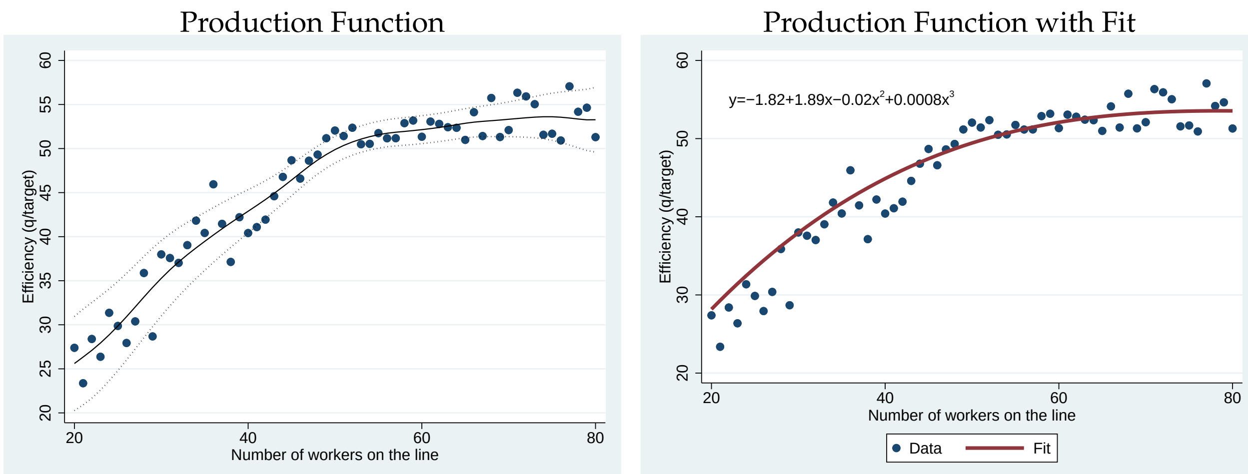
	Any number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	568.7733	124.3410	120.7499
	(0.0241) **	(0.0446) **	(0.0431) **
	[0.0237] **	[0.0445] **	[0.0432] **
	{0.1166}	{0.1130}	{0.1081}
log(Maturity of relationship)	1.8444	4.4665	4.4677
	(0.0000) ***	(0.0000) ***	(0.0000) ***
	[0.0000] ***	[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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. 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 managers 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.

6 Simulations

In this section, 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 problem resulting from idiosyncratic absenteeism realizations across lines. To do so, we first estimate a reduced-form production function. We first plot efficiency (output) on the number of workers on the production line (input). The first panel of Figure 8 shows that relationship. Consistent with what we found before in Figure 3, the relationship is concave. Efficiency increases sharply until 50-55 workers and is almost constant afterwards. We then approximate this empirical function by regressing efficiency on a 3rd degree polynomial in the number of workers on the line and on our usual fixed effects. The second panel of Figure 8 shows the average predicted efficiency produced by a 3rd degree polynomial estimate.

Figure 8: Average efficiency by the number of workers on the line



Note: In the first panel, we plot the average efficiency by the number of workers on the line across managers and the 95% confidence interval for this average. For ease of presentation, we censor the figure at 20 and 80 workers on the line. Less than 5% of observations have fewer than 20 or more than 80 workers on the line. In the second panel, we also estimate a functional form for the relationship between efficiency and the number of workers on the line by regressing daily efficiency on a 3rd degree polynomial in the number of workers on the line and manager, unit, year, month, and day of the week fixed effects. We find the following functional form: efficiency= $-1.82 + 1.89x - 0.02x^2 + 0.0008x^3$ where x is the number of workers on the line. We compute the predicted efficiency given by the polynomial for every manager and days. We plot the average predicted efficiency against the number of workers on the line. The estimation is done over all manager-day observations, but we censor the figure at 20 and 80 workers on the line.

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 the flow of workers across new relationship pairs, further decreasing 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. We iterate this procedure for a given number of days to estimate the mean and standard error of the impact estimate.

In all simulations, we assume the production function that is implied by Figure 8. That is, we assume that the relationship between the number of workers on the line and efficiency is approximated by the 3rd degree polynomial displayed in the second panel of Figure 8. We also assume throughout that the production function remains fixed before and after the counterfactual policy change.

6.1 Benchmarks

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

6.1.1 No redistribution

We begin by asking what the simulated gains to relationships 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. 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. Applying the procedure outlined above but shutting down redistribution, we find that efficiency falls by 0.90 percent, from 49.13% (SE 0.004) to 48.69% (SE 0.005).[39]

Note that to compute the standard errors, we draw 100 production days (without replacement) at random. For each day, we compute the predicted efficiency with the current trades by plugging the number of workers on the line into the estimated production function. To compute the scenario without trade, we use the number of home line workers in the unit 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.

6.1.2 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. In this simulation, we compute the loss (gain) of every line in the unit from losing (gaining) 1 worker. The line with the smallest loss then gives that worker to the line with the largest gain. We repeat that exercise as long as the smallest loss is less than the largest gain.[40] We draw 100 days and

[39] All changes in predicted efficiency presented below represent significant differences at the 1% level.

[40] We repeat that exercise for increments of 0.1, 0.01, and 0.001 workers to reflect the fact that workers can be traded for a fraction of a day and fully exploit the gains from trade.

perform this procedure on each day; we then repeat this exercise 100 times to compute standard errors around simulated treatment estimates. Predicted productivity is 49.13% (SE 0.004) prior to redistribution and 49.90% (SE 0.007) after. This change represents a 1.58 percent increase in aggregate efficiency.

6.1.3 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 1.08 percent (from 49.13% (SE 0.004) to 49.66% (SE 0.004)).

6.1.4 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 traded just like in subsection 6.1.2. We find that the average efficiency increases by 3.43% from 49.13 (SE 0.004) to 50.82% (SE 0.013)

6.1.5 Reducing physical distance plus optimal redistribution

In the last 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 way. A policy that the firm could implement would be to introduce an app in which managers could log the number of workers they need or are willing to spare.[41] Excess workers would then be assigned optimally to the lines most in need. Such a tool, if carefully implemented, could eliminate the need for interactions between the managers which would effectively eliminate the negative effect of physical and identity-based distances.

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 5, we find that lines would borrow on average 73.36% more if the distance would fall to 1 foot on average. [42] 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 find what would be this average if it were to increase by 73.36%. We trade workers

[41] The identity of the managers could be anonymous to other managers, but verifiable by upper-level managers in order for the latter to audit the managers an elicit truthful revelations of the need for and excess of workers.

[42] 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.

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 subsection 6.1.2. We repeat the exercise 100 times to compute the standard errors. We find that reducing distance would increase efficiency by 1.49% on average (from 49.13% (SE 0.004%) to 49.87% (SE 0.005%)).

6.1.6 Reducing demographic distance plus optimal redistribution

Finally, 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 5, 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.[43] 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 B. 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.[44] 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 find 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 0.9% from 49.13 (SE 0.004) to 49.58% (SE 0.005).

Figure 9 plots the average efficiency under all simulations on the left y-axis and shows the percentage increase or decrease from the baseline scenario given by the black line above each marker.[45] 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 improving the trades between the managers. In fact, the current level of trade exploits less than 40% of the potential efficiency gains.[46] While going from no trade to optimal trade increases efficiency by

[43] 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.

[44] All else equal, in demographically dissimilar pairs, the predicted borrowing is $\theta^1_{ij} = e^{X\beta-0.3195\times 1} = e^{X\beta}e^{-0.3195}$ and in similar pairs, $\theta^0_{ij} = e^{X\beta-0.3195\times 0} = e^{X\beta}$, 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%.

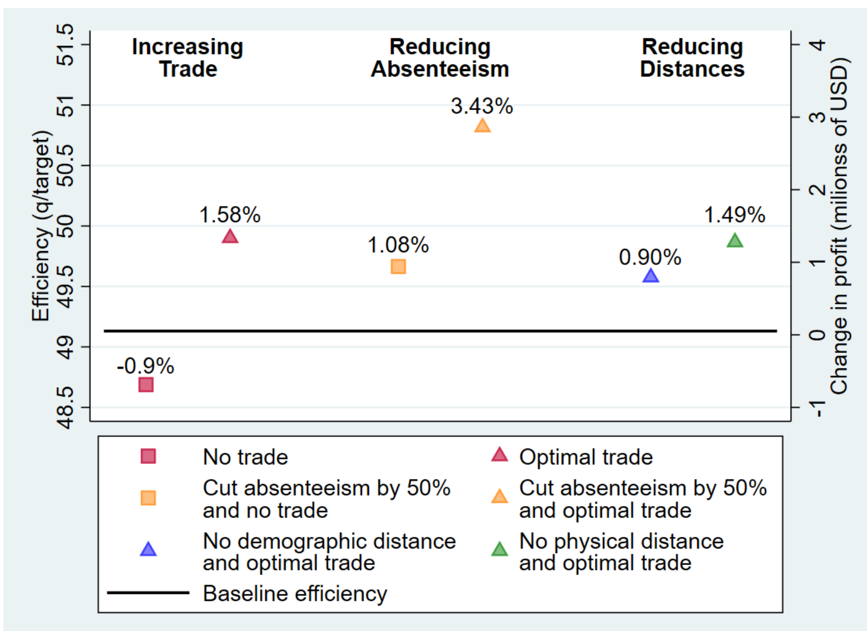
[45] All differences between the point estimates are significant at the 1% level. The 99% confidence bands are smaller than the marker size and are not displayed on the graph.

[46] (base line-no trade)/(optimal trade-no trade)=(49.13-48.69)/(49.9-48.69)=0.364.

2.3-2.5%,[47] cutting absenteeism by half has a smaller effect in the range of 1.8-2%.[48] Moreover, the last two simulations reveal that demographic differences and physical distance put large barriers on trade. Indeed, reducing demographic differences and physical distance could allow the firm to exploit 57% and 94% of the gains realized under optimal trading, respectively.

Finally, we compute back-of-the-envelope profit changes that would result from these changes in misallocation. The company makes approximately 1 billion US dollars in revenue each year and every percentage point increase in efficiency translates into an 0.001875-0.0025 percentage point increase in profit, or 1.87-2.50 million dollars per year (Adhvaryu et al., 2018b). On the right vertical axis of Figure 9, we plot the increase (or decrease) in profit from baseline for each simulation using the most conservative estimates. We find that if the firm could reach the optimal trading equilibrium, profit would increase by \$1.44 million per year under the current level of absenteeism and by \$3.16 million per year if absenteeism also falls by half. Hence, the results suggest that fostering an environment that promotes partnerships can benefit the firm greatly.

Figure 9: 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 (second marker). Then, we compute the efficiency gain when absenteeism falls by half for every line and managers do not trade (third marker), and when workers are traded optimally (fourth marker).Finally we compute the gain in efficiency when workers are traded optimally and demographic distances are eliminated (fifth marker), and when the average physical distance falls to 1 feet (sixth marker).

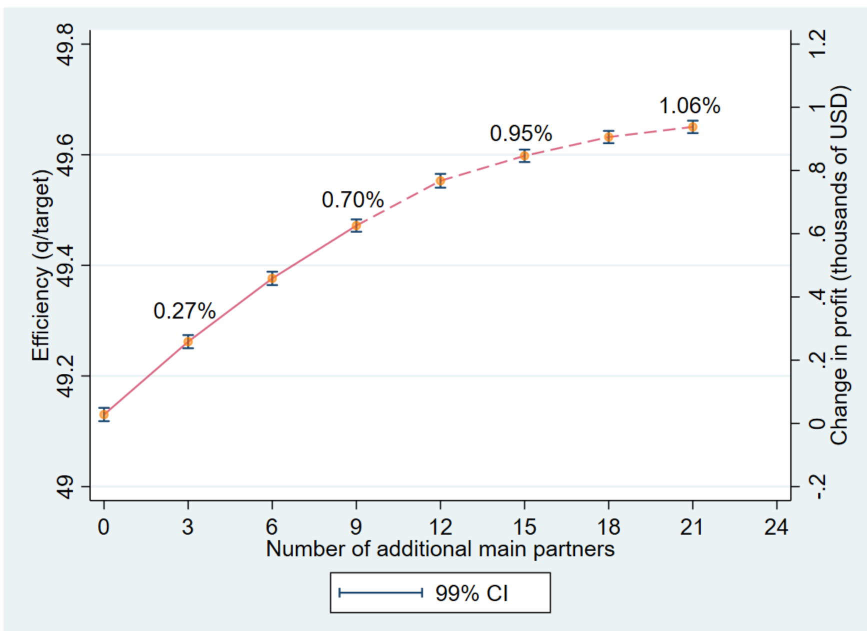
[47]Under the curent level of absenteeism, going from the no trade equilibrium to the optimal trade equilibrium increases efficiency by $100 \times \frac{49.9-48.69}{48.69}$ =2.49%. Doing the same when absenteeism falls by half leads to an increase of 2.32%

[48]Going from the current level of absenteeism to the a 50% reduction of absenteeism within the no trade equilibrium increases efficiency by $100 \times \frac{49.66-48.69}{48.69}$ =2.01% and by 1.83% within the optimal trade equilibrium.

6.1.7 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 5 and include a dummy variable for whether the partner is one of the manager's 3 main partners. The results are presented in Table B2 of Appendix B. Using the estimates in column 3, we find that a manager borrows 51% more from his 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 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.

Figure 10: 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 managers 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.

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 managers. 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 10.

We find that 3 additional main partners increase efficiency by 0.27% and that when all partners are main partners (21 additional main partners on average across all units), efficiency increases by 1.06% from 49.13% (SE 0.004) to 49.26% (SE 0.005) and 49.65% (SE 0.004) respectively. These results suggest that if the firm were to increase partnerships to a maximum, it could achieve approximately 70% of the efficiency gains possible under the first best scenario where there are no constraints and all workers are traded optimally. 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. If the firm were able to increase the number of main partners by just 3 (or 6) main partners, we estimate that its profit could increase by 247 thousand dollars per year (or 462 thousand dollars). This suggests that overall, relational contracts are highly valuable for the firm.

7 Conclusion

Relational contracts form the basis of much of the theory of organizational economics. They are what enable firms to remain productive in spite of the infeasibility of formal contract specification and enforcement among coworkers. Yet despite this fundamental role, we have little rigorous empirical evidence on the function and importance of relational contracts in the real world. Our study aims to fill this gap by leveraging a unique dataset of managers' interactions in a garment manufacturing firm in India. We focus on the role of these interactions in dealing with the key challenge of mitigating the impacts of worker absenteeism. 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. Next we study how managers leverage relationships to lend and borrow workers in a manner consistent with canonical models of relational contracting.

The two key facts to emerge from this analysis are the following. First, 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; they transact very sparingly with other managers. This results in many potentially beneficial transfers being left unrealized. Second, managers are significantly more likely to develop relationships with managers who are both physically close (on the factory floor) as well as similar in terms of identity characteristics. This latter analysis suggests that dyad-specific costs of transacting may serve as meaningful barriers to relationship formation and maturity.

Last, we explore counterfactual simulations in which the firm invests in creating additional relationships. We find substantial gains to mature relationship formation. The magnitudes of the productivity effects in this analysis suggest that worker misallocation (conditional on realizations of absenteeism) plays as central a role in determining productivity as does the problem of absenteeism itself. While in these simulations we remain agnostic as to the specific policies that could create more close relationships among managers, our results offer some clues as to potential policy solutions that may be effective. For example, since physical distance is key, a redesign of production lines on factory floors may bring more managers closer together. Similarly, given that identity characteristics are salient, more homogeneous assignment of managers to factory floors might increase the number of mature relationships. Finally, while centralization of assignment of available workers to lines is likely very difficult for reasons discussed earlier in the paper, hiring an "intermediary" whose job it is to facilitate quick transactions by reducing costs of interacting among managers (or providing a technological solution that enables managers to participate in a daily internal market at low cost) may also decrease the degree of aggregate misallocation. We leave the assessment of the effectiveness of these policies to future work in this area.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–334.

Adhvaryu, A., Bassi, V., Nyshadham, A., and Tamayo, J. (2019a). No line left behind: Assortative matching inside the firm. *Available at SSRN 3462873*.

Adhvaryu, A., Chari, A. V., and Sharma, S. (2013). Firing costs and flexibility: evidence from firms' employment responses to shocks in india. *Review of Economics and Statistics*, 95(3):725–740.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2018a). The light and the heat: Productivity co-benefits of energy-saving technology. Technical report, National Bureau of Economic Research.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2018b). The skills to pay the bills: Returns to on-the-job soft skills training. Technical report, National Bureau of Economic Research.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2019b). Management and shocks to worker productivity. Technical report, National Bureau of Economic Research.

Adhvaryu, A., Nyshadham, A., and Tamayo, J. (2019c). Managerial quality and productivity dynamics. Technical report, Mimeo, University of Michigan, Boston College and Harvard Business School.

Amodio, F. and Di Maio, M. (2017). Making do with what you have: Conflict, input misallocation and firm performance. *The Economic Journal*, 128(615):2559–2612.

Amodio, F. and Martinez-Carrasco, M. A. (2018). Input allocation, workforce management and productivity spillovers: Evidence from personnel data. *The Review of Economic Studies*, 85(4):1937–1970.

Anderson, J. E. (2011). The gravity model. *Annual Review of Economics*, 3(1):133–160.

Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American economic review*, 93(1):170–192.

Atalay, E., Hortaçsu, A., Li, M. J., and Syverson, C. (2019). How wide is the firm border? *The Quarterly Journal of Economics*, 134(4):1845–1882.

Atkin, D. and Khandelwal, A. (2019). How distortions alter the impacts of international trade in developing countries. Technical report, National Bureau of Economic Research.

Baker, G., Gibbons, R., and Murphy, K. J. (1994). Subjective performance measures in optimal incentive contracts. *The Quarterly Journal of Economics*, 109(4):1125–1156.

Baker, G., Gibbons, R., and Murphy, K. J. (2001). Bringing the market inside the firm? *American Economic Review*, 91(2):212–218.

Baker, G., Gibbons, R., and Murphy, K. J. (2002). Relational contracts and the theory of the firm. *Quarterly Journal of Economics*, 117(1):39–84.

Bandiera, O., Barankay, I., and Rasul, I. (2007). Incentives for managers and inequality among workers: evidence from a firm-level experiment. *The Quarterly Journal of Economics*, 122(2):729–773.

Bandiera, O., Barankay, I., and Rasul, I. (2009). Social connections and incentives in the workplace: Evidence from personnel data. *Econometrica*, 77(4):1047–1094.

Bandiera, O., Barankay, I., and Rasul, I. (2010). Social incentives in the workplace. *The review of economic studies*, 77(2):417–458.

Bandiera, O., Barankay, I., and Rasul, I. (2013). Team incentives: Evidence from a firm level experiment. *Journal of the European Economic Association*, 11(5):1079–1114.

Banerjee, A. and Duflo, E. (2006). Addressing absence. *Journal of Economic perspectives*, 20(1):117–132.

Banerjee, A. V. and Duflo, E. (2000). Reputation effects and the limits of contracting: A study of the indian software industry. *The Quarterly Journal of Economics*, 115(3):989–1017.

Bloom, N., Sadun, R., and Van Reenen, J. (2016). Management as a technology? Technical report, National Bureau of Economic Research.

Bloom, N., Sadun, R., and van Reenen, J. M. (2010). Recent advances in the empirics of organizational economics. *Annual Review of Economics*, 2(1):105–137.

Bloom, N. and Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics*, 122(4).

Bloom, N. and Van Reenen, J. (2011). Human resource management and productivity. *Handbook of labor economics*, 4:1697–1767.

Board, S. (2011). Relational contracts and the value of loyalty. *American Economic Review*, 101(7):3349–67.

Boudreau, L. (2020). Multinational enforcement of labor law: Experimental evidence from bangladeshs apparel sector.

Bryan, G. and Morten, M. (2019). The aggregate productivity effects of internal migration: Evidence from indonesia. *Journal of Political Economy*, 127(5):2229–2268.

Burgess, S., Propper, C., Ratto, M., Kessler Scholder, S. v. H., and Tominey, E. (2010). Smarter task assignment or greater effort: the impact of incentives on team performance. *The Economic Journal*, 120(547):968–989.

Cajal-Grossi, J., Macchiavello, R., and Noguera, G. (2019). International buyers' sourcing and suppliers' markups in bangladeshi garments.

Chaney, T. (2018). The gravity equation in international trade: An explanation. *Journal of Political Economy*, 126(1):150–177.

Chassang, S. (2010). Building routines: Learning, cooperation, and the dynamics of incomplete relational contracts. *American Economic Review*, 100(1):448–65.

Chaudhury, N., Hammer, J., Kremer, M., Muralidharan, K., and Rogers, F. H. (2006). Missing in action: teacher and health worker absence in developing countries. *Journal of Economic perspectives*, 20(1):91–116.

Chetverikov, D. and Wilhelm, D. (2017). Nonparametric instrumental variable estimation under monotonicity. *Econometrica*, 85(4):1303–1320.

Coate, S. and Ravallion, M. (1993). Reciprocity without commitment: Characterization and performance of informal insurance arrangements. *Journal of development Economics*, 40(1):1–24.

Duflo, E., Hanna, R., and Ryan, S. P. (2012). Incentives work: Getting teachers to come to school. *American Economic Review*, 102(4):1241–78.

Frederiksen, A., Kahn, L. B., and Lange, F. (2017). Supervisors and performance management systems. Technical report, National Bureau of Economic Research.

Friebel, G., Heinz, M., Krüger, M., and Zubanov, N. (2017). Team incentives and performance: Evidence from a retail chain. *American Economic Review*, 107(8):2168–2203.

Gibbons, R. and Henderson, R. (2012a). Relational contracts and organizational capabilities. *Organization Science*, 23(5):1350–1364.

Gibbons, R. and Henderson, R. (2012b). *What do managers do?: Exploring persistent performance differences among seemingly similar enterprises*.

Gibbons, R. and Roberts, J. (2012). *The handbook of organizational economics*. Princeton University Press.

Gibbons, R. and Waldman, M. (2004). Task-specific human capital. *American Economic Review*, 94(2):203–207.

Gosnell, G. K., List, J. A., and Metcalfe, R. D. (2019). The impact of management practices on employee productivity: A field experiment with airline captains. Technical report, National Bureau of Economic Research.

Hansman, C., Hjort, J., León, G., and Teachout, M. (2017). Vertical integration, supplier behavior, and quality upgrading among exporters. Technical report, National Bureau of Economic Research.

Helper, S. and Henderson, R. (2014). Management practices, relational contracts, and the decline of general motors. *Journal of Economic Perspectives*, 28(1):49–72.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, 129(4):1899–1946.

Hoffman, M. and Tadelis, S. (2018). People management skills, employee attrition, and manager rewards: An empirical analysis. Technical report, National Bureau of Economic Research.

Holmstrom, B. R. and Tirole, J. (1989). The theory of the firm. *Handbook of industrial organization*, 1:61–133.

Johnson, S., McMillan, J., and Woodruff, C. (2002). Courts and relational contracts. *Journal of Law, Economics, and organization*, 18(1):221–277.

Khwaja, A. I., Mian, A., and Qamar, A. (2008). The value of business networks. *Unpublished manuscript. Retrieved from http://cei. ier. hit-u. ac. jp/Japanese/events/documents/AsimKhwaja_ NetworksImpact. pdf*.

Kremer, M. (1993). The o-ring theory of economic development. *The Quarterly Journal of Economics*, 108(3):551–575.

Kremer, M., Chaudhury, N., Rogers, F. H., Muralidharan, K., and Hammer, J. (2005). Teacher absence in india: A snapshot. *Journal of the European Economic Association*, 3(2-3):658–667.

Lafontaine, F. and Slade, M. (2007). Vertical integration and firm boundaries: The evidence. *Journal of Economic Literature*, 45(3):629–685.

Lazear, E. P. and Oyer, P. (2007). Personnel economics. Technical report, National Bureau of economic research.

Lazear, E. P. and Shaw, K. L. (2007). Personnel economics: The economist's view of human resources. *Journal of economic perspectives*, 21(4):91–114.

Lazear, E. P., Shaw, K. L., Stanton, C. T., et al. (2015). The value of bosses. *Journal of Labor Economics*, 33(4):823–861.

Levin, J. (2003). Relational incentive contracts. *American Economic Review*, 93(3):835–857.

Levitt, S. D., List, J. A., and Syverson, C. (2013). Toward an understanding of learning by doing: Evidence from an automobile assembly plant. *Journal of Political Economy*, 121(4):643–681.

Macchiavello, R., Menzel, A., Rabbani, A., and Woodruff, C. (2020). Challenges of change: An experiment promoting women to managerial roles in the bangladeshi garment sector.

Macchiavello, R. and Miquel-Florensa, J. (2017). Vertical integration and relational contracts: Evidence from the costa rica coffee chain.

Macchiavello, R. and Morjaria, A. (2015). The value of relationships: evidence from a supply shock to kenyan rose exports. *American Economic Review*, 105(9):2911–45.

Macchiavello, R. and Morjaria, A. (2017). Competition and relational contracts: evidence from rwanda's coffee mills.

MacLeod, W. B. and Malcomson, J. M. (1989). Implicit contracts, incentive compatibility, and involuntary unemployment. *Econometrica: Journal of the Econometric Society*, pages 447–480.

McKenzie, D. and Woodruff, C. (2016). Business practices in small firms in developing countries. *Management Science*.

McMillan, J. and Woodruff, C. (1999). Interfirm relationships and informal credit in vietnam. *The Quarterly Journal of Economics*, 114(4):1285–1320.

WTO (2018). World trade statistical review 2018. Technical report.

Yang, H. (2013). Nonstationary relational contracts with adverse selection. *International Economic Review*, 54(2):525–547.

ONLINE APPENDIX

A Robustness to Including all Dyads

Table A1: Tests of model predictions robustness

	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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. 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 managers 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 A1, 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.

B Demographic Binary and Main Trading Partners

Table B1: Tests of model predictions 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. 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 managers 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 B2: Tests of model predictions 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. 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 managers 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.

C 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., 2018a) and air pollution (Adhvaryu et al., 2019b). It is also possible that on excessively hot or polluted days more workers decide to stay home. Similarly, a manager may attempt to increase his 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, 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.[49] 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.[50]

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.[51] 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.

The following table is the instrumental variable of the specification presented in Table 4, 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.

[49] 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.

[50] 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.

[51] 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.

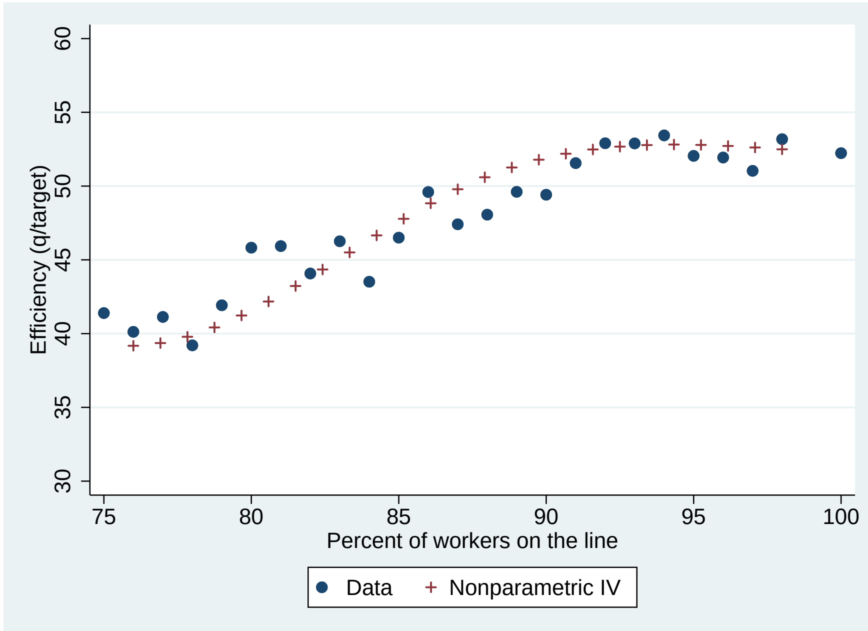
Table C1: Productivity losses from absenteeism with instrument

	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 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.

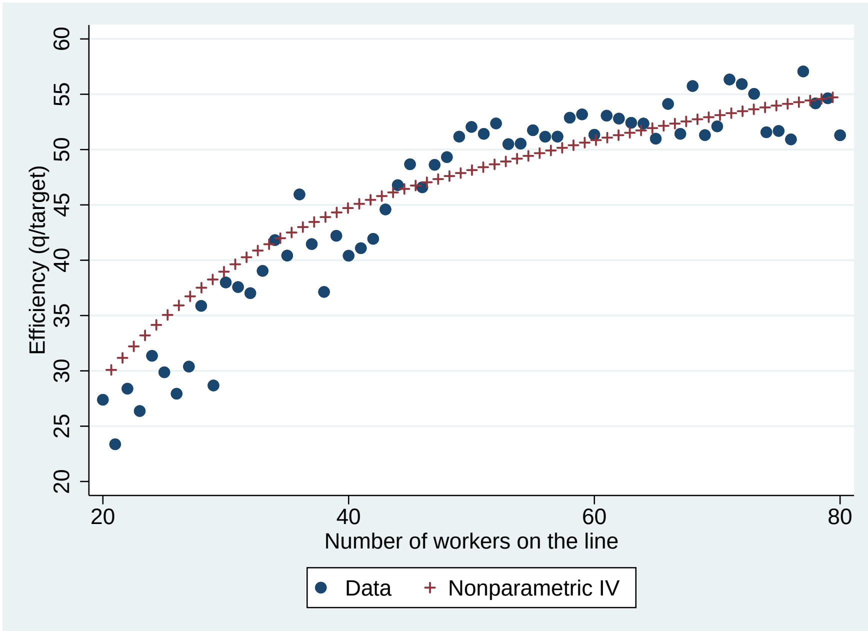
To confirm that the relationship between workers present on the line and efficiency depicted in Figure 3 is preserved when leveraging the variation in absenteeism derived from the instrument, we plot the reduced form relationship using a nonparametric IV fit in Figure C1. That is, we first compute the average efficiency at the line level by 1% bins of the percentage of workers on the line just as we did in Figure 3. 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 C1 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. The same can be said about the production function as can be seen from Figure C2.

Figure C1: 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.

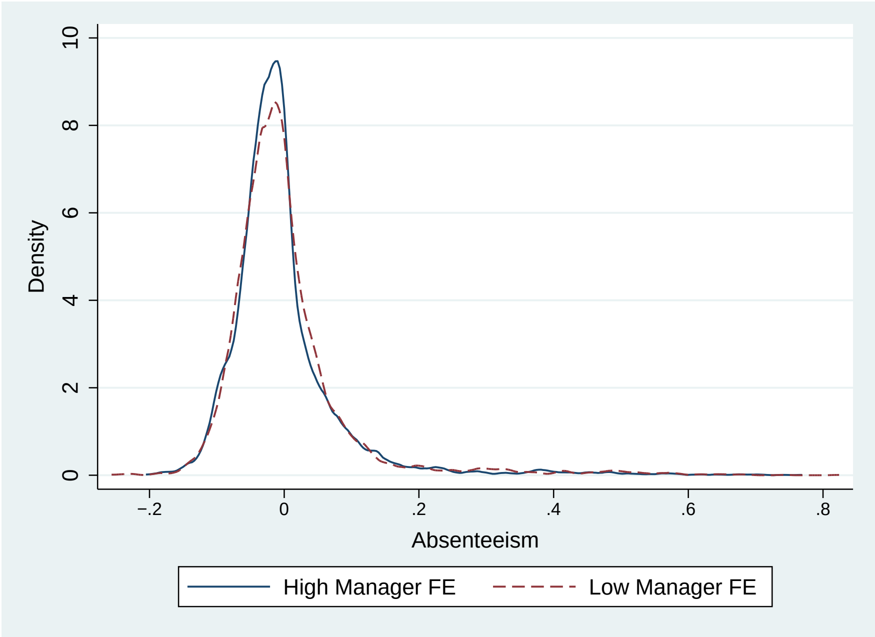
Figure C2: Production function with nonparametric IV fit



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 number of workers working on the line (in 1% bins). 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, day of the week, 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 C3, 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 C3: Distribution of residual absenteeism by manager FE



Note: We regress the log efficiency on unit, year, month, day of the week, and style fixed effects and recover the managers' 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. We partial out the same fixed effects from manager-day absenteeism and plot the distribution of residual absenteeism against the managers' efficiency status.

D Proofs

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

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

subject to the incentive compatibility constraint (2). 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 (2) is satisfied. Second, note that the domain,

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

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

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

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

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

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

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

as long as

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

is satisfied. Therefore, $\theta^*_{ij} = H\left(y_i,c_{ij},\delta\left(U^R(\boldsymbol{\theta}^*)-V\right)\right)$ if (D.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 $\hat{\theta}_{ij} > H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)$, then in this case we show that $\theta^*_{ij} = H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)$; $ii)$ suppose that $\hat{\theta}_{ij} \leq H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)$ then we show that $\theta^*_{ij} = \hat{\theta}_{ij}$.

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

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

Note that $f > 0$, then

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

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

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

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

Therefore, the contract defined by $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ belongs to the set Ω.[52] Note that

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

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

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 $U^R_0\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0\right)$ subject to the incentive compatibility constraints

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

(1) for all t, where $U_0^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_0)$ is the present value of the expected utility over time, defined in equation (D.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 $i,j \in \mathcal{K}$, 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.[53]

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, $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$; 2) we show that $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$ is increasing with respect to γ_t.[54]

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

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

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

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

is satisfied for positive values of $\theta_{ij,t}$ and $\theta_{ij,t+1}$.[55]

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 $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$, we will recursively apply (D.7). The term $\tilde{\gamma}_t$ in the expression (D.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 $(1-\gamma_t)\rho$. Then, $U_t^R(\boldsymbol{\theta}_t;\gamma_t)$ can be expressed as

$$
U_t^R(\boldsymbol{\theta}_t;\gamma_t) = \tilde{\gamma}_t F(\boldsymbol{\theta}_t) + C(V;\gamma_t) + g(\boldsymbol{y};\gamma_t) + \tilde{\gamma}_t\delta U_{t+1}^R(\boldsymbol{\theta}_{t+1};\gamma_{t+1}),
\tag{D.9}
$$

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

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

[55]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.

where

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

Note that (D.9) follows from: (i) $\pi_{ij} = \pi_{ji}$ for all $i, j \in \mathcal{K}$; (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 (D.9) to obtain an explicit equation for $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$. Note that after two iterations we have

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

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

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

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

2) We show now that $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$ is increasing with respect to γ_t. First, note that $F(\cdot)$ has a global maximum at $\theta_{ij,t} = \hat{\theta}_{ij}$, thus, for any $(i,j) \in S_1$

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

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:

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

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

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

where $E_{\pi_{ij}}\left[f\left(y_i\right)\right]=\sum_{S_1} \pi_{ij}\left[f\left(y_i\right)+f\left(y_j\right)\right]+\sum_{S_3 \cup S_4} \pi_{ij} f\left(y_i\right)$.[56]

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

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

Now, the left hand side of (D.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 (D.15) is

$$
\sum_{S_1} \pi_{ij}\left[2 f\left(\frac{y_i+y_j}{2}\right)-f\left(y_i\right)-f\left(y_j\right)-c_{ij}\right]-\delta V>0. \tag{D.16}
$$

By continuity there exists a constant $\underline{\theta}$, independent of k, such that for any $\theta_{ij,t+k} \in (\underline{\theta}, \hat{\theta}_{ij})$, (D.15) holds. Which proves that expression (D.13) is positive for any $k \in \mathbb{N} \cup \{0\}$, thus, $U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t\right)$ 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 $i,j \in \mathcal{K}$, 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 $U_0^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0\right)$ subject to the IC constraints. Note that the IC constraint increases at every step t, then by the monotonicity of $U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t\right)$ and (D.11), $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ must be monotonic.

Proof of Prediction 1. Let $y_i^1 > y_i^2 > y_j$ be three different home line levels in $\{y_1, \ldots, y_n\}$. Let θ_{ij}^1 and θ_{ij}^2 be the respective optimal allocations from the stationary contract $\boldsymbol{\theta}^*$. Given that the first best allocation $\hat{\theta}$ is never achieved, then $\theta_{ij}^1 < \hat{\theta}_{ij}^1$ and $\theta_{ij}^2 < \hat{\theta}_{ij}^2$. From Proposition 1,

$$
\theta_{ij}^1 = H\left(y_i^1, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right)-V\right)\right),
$$

[56] Note that for $k=0$, (D.13) is

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

and

$$\theta_{ij}^2 = H\left(y_i^2, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right).$$

We show that $\theta_{ij}^1 > \theta_{ij}^2$. From equation (D.3) it follows that H is strictly increasing on y as long as $w > c$. Since $y_i^l > y_j$ for $l = 1, 2$ then $\theta_{ij}^l > 0$ and because

$$\theta_{ij}^l > 0 \iff f(y_i^l) - f(y_i^l - \theta_{ij}^l) > 0,$$

we have that $\delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right) > c_{ij}$. Thus, H is strictly increasing with respect to y and

$$\theta_{ij}^1 = H(y_i^1, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)) > H(y_i^2, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)) = \theta_{ij}^2,$$

concluding the proof.

Proof of Prediction 2. Let $c_{ij}^1 < c_{ij}^2$ two different transaction cost. If θ_{ij}^1 and θ_{ij}^2 are the stationary relational contracts associated with each c_{ij}^1, c_{ij}^2, respectively, then we show that $\theta_{ij}^1 > \theta_{ij}^2$. Given that the first best allocation $\hat{\theta}$ is never achieved for c_{ij}^1 nor c_{ij}^2, then $\theta_{ij}^1 < \hat{\theta}_{ij}$ and $\theta_{ij}^2 < \hat{\theta}_{ij}$. From Proposition 1

$$\theta_{ij}^1 = H\left(y_i, c_{ij}^1, \delta\left(U^R\left(\boldsymbol{\theta}^1\right) - V\right)\right),$$

and

$$\theta_{ij}^2 = H\left(y_i, c_{ij}^2, \delta\left(U^R\left(\boldsymbol{\theta}^2\right) - V\right)\right).$$

Note that

$$\underbrace{\left\{\theta_{ij} \in \mathbb{R}^d | f\left(y_i\right) - f\left(y_i - \theta_{ij}\right) + c_{ij}^2 \le \delta\left(U^R\left(\boldsymbol{\theta}\right) - V\right)\right\}}_{A_2}$$
$$\subseteq \underbrace{\left\{\theta_{ij} \in \mathbb{R}^d | f\left(y_i\right) - f\left(y_i - \theta_{ij}\right) + c_{ij}^1 \le \delta\left(U^R\left(\boldsymbol{\theta}\right) - V\right)\right\}}_{A_1},$$

which implies that $\Omega_2 \subseteq \Omega_1$. Thus $U^R(\boldsymbol{\theta}^2) \le U^R(\boldsymbol{\theta}^1)$ (since $\boldsymbol{\theta}^1$ is being chosen from a larger set) and

$$\delta\left(U^R\left(\boldsymbol{\theta}^2\right) - V\right) \le \delta\left(U^R\left(\boldsymbol{\theta}^1\right) - V\right).$$

From (D.3) it follows that H is strictly increasing on w and strictly decreasing with respect to c, therefore

$$\theta_{ij}^2 = H\left(y_i, c_{ij}^2, \delta\left(U^R\left(\boldsymbol{\theta}^2\right) - V\right)\right) < H\left(y_i, c_{ij}^1, \delta\left(U^R\left(\boldsymbol{\theta}^1\right) - V\right)\right) = \theta_{ij}^1,$$

concluding the proof. Note that θ_{ij}^1 increases with respect to θ_{ij}^2 directly by the effect of c_{ij}^1, but also indirectly by effect on the utility level $U^R(\boldsymbol{\theta}^1)$.

Proof of Prediction 3. As in the previous prediction, let $c_{ij}^1 < c_{ij}^2$ two different transaction cost. Let θ_{ij}^1 and θ_{ij}^2 the stationary relational contracts associated with each c_{ij}^1, c_{ij}^2, respectively. From Prediction 2, we know that $\theta_{ij}^1 > \theta_{ij}^2$. Which means that as long as the first best allocation $\hat{\theta}$ is never achieved then

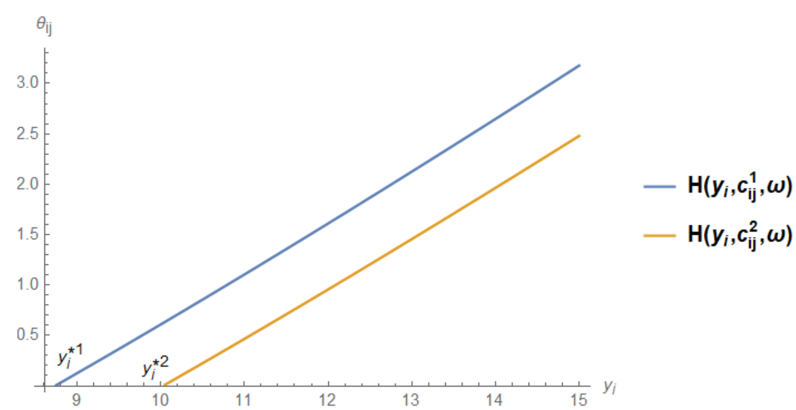
$$\theta_{ij}^1 = H\left(y_i, c_{ij}^1, \delta\left(U^R\left(\boldsymbol{\theta}^1\right) - V\right)\right) > H\left(y_i, c_{ij}^2, \delta\left(U^R\left(\boldsymbol{\theta}^2\right) - V\right)\right) = \theta_{ij}^2.$$

The previous inequality holds for any y_i that satisfies

$$f(y_i) + c_{ij}^1 > \delta\left(U^R\left(\boldsymbol{\theta}^1\right) - V\right) > \delta\left(U^R\left(\boldsymbol{\theta}^2\right) - V\right),$$

recall that $U^R(\cdot)$ is increasing with respect to θ_{ij} by (D.6). Now let y_i^{*1} and y_i^{*2} be the points such that $H\left(y_i^{*1}, c_{ij}^1, \delta\left(U^R\left(\mathbf{0}\right) - V\right)\right) = 0 = H\left(y_i^{*2}, c_{ij}^2, \delta\left(U^R\left(\mathbf{0}\right) - V\right)\right)$ (note that by (D.3) and continuity they must exists). Also note that H is strictly increasing with respect to y (see Prediction 1), which implies that $y_i^{*1} < y_i^{*2}$ (see Figure D1).

Figure D1: y_i^{*1} vs. y_i^{*2}



Proof of Prediction 4. The proof of this prediction follows from the proof of Proposition 2: we showed that $U_t^R\left(\{\boldsymbol{\theta}_t\}_t; \gamma_t\right)$ is strictly increasing with respect to γ_t. Then, an optimal dynamic relational contract must be monotonic, i.e. it satisfies $\theta_{ij,t}^* \leq \theta_{ij,t+1}^*$ for all $t \in \mathbb{N}$.

Proof of Prediction 5. From the proof of Proposition 2, $U_t^R\left(\{\boldsymbol{\theta}_t\}_t; \gamma_t\right)$ is strictly increasing with respect to γ_t and that an optimal dynamic relational contract must be monotonic. These two facts and equation (D.8) show that as the maturity of the relationship increases the frequency of transfers between i and j increase.

E 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 her 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 E1). We do a similar updating when a worker is working on her home line of the previous trimester a few days in the current trimester where her home line changes (see Table E2). We carefully take into account days traded and days absent in this exercise.

Table E1: 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 E2: 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 her home line for those consecutive days to be the line where she 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. She spends 45 days on line 1. Therefore, line 1 is currently her home line given our definition. She spends 32 (40%) near consecutive days on line 2, but she is seen on line 3 three days in that period. Even if the 32 days were not consecutive, she was clearly assigned to line 2 over that period and was traded 3 days to line 3. Therefore, we update her home line over that period to be line 2 (see Table E3). A similar adjustment is done if the worker is absent (see table E4 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 E3: 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 E4: 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