The Ties That Bind Us: Social Networks and Productivity in the Factory*

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Abstract

We use high frequency worker level productivity data from garment manufacturing units in India to study the effects of caste-based social networks on individual and group productivity when workers are complements in the production function but wages are paid at the individual level. Using exogenous variation in production line composition for almost 35,000 worker-days, we find that a 1 percentage point increase in the share of own caste workers in the line increases daily individual productivity by at least 9 percentage points. The lowest performing worker increases her effort by more than 12 percentage points when the production line has a more homogeneous caste composition. Production externalities, that impose financial costs due to worker's poor performance on co-workers within her social network, can explain our findings. Our results suggest that even in the absence of explicit group-based financial incentives, social networks can be leveraged to improve both worker and group productivity.

Keywords: caste, social networks, labor productivity, assembly lines, India
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1 Introduction

While much of the literature on the manufacturing sector has focused on productivity differentials across firms (Bloom et al. (2013)), in several industries production processes are organised in teams, such as assembly lines. Team productivity often varies significantly not just across firms but also within the same manufacturing units.[1] In our setting of the labor intensive garment industry in India, average team productivity can vary by almost 30 percentage points (pp) between the least and most productive teams or lines in the same manufacturing plant. This variation in productivity across teams is accompanied by equally large variation across workers within a team, with the least productive worker being more than 90 pp less efficient than the most productive worker.

Research providing micro econometric evidence on determinants of worker productivity under team production is, however, scarce. A majority of the existing studies estimate individual worker performance under either individual piece rate payments (performance pay) or team based incentives when workers are substitutes in the production function. The determinants of coordination amongst workers in large assembly lines within firms has not been explored in the literature. We attempt to fill this gap by analysing the role of workers' caste-based social networks in explaining the large variation in individual and team output across production lines within garment manufacturing units in India. With millions of workers worldwide (Chang et al. (2016), GOI (2018)), labor-intensive garment manufacturing is a natural choice for advancing our understanding of worker performance within firms.

Given the nature of the production function in assembly lines, where comple-

[1] In an ongoing project on garment productivity (`https://www.qeh.ox.ac.uk/content/readymade-garment-productivity-project`), Macchivello, Menzel, Rabbani and Woodruff find significant dispersion of productivity within factories in a sample of 100 factories in Bangladesh - production lines at the 90th percentile are 50% more efficient than those at the 10th percentile.

mentarities between workers generate externalities in the production process and the total output of the team is determined by the minimum individual output, the worker composition of these teams can play a significant role in determining both group and firm output. Using high-frequency data that include detailed information on the daily productivity of individual workers, their production lines, and the caste composition of the workers' lines on each production day in the stitching department of two garment factories in the National Capital Region of Delhi, we follow 1744 workers over 31 work days, giving us information for 34,641 worker-days. Our identification strategy relies on exogenous variation in the daily worker composition of production lines due to unanticipated worker absenteeism to estimate the causal impact of the proportion of own-caste workers in a production line on individual and line productivity.

Our findings suggest that a 1 pp increase in the strength of the workers' social network - the proportion of workers belonging to own caste - in the line on a work day, raises workers' own productivity by at least 9 pp. We calculate the caste-concentration index of the line and aggregate the data to the line level to find that the least efficient worker's productivity rises by over 12 pp while the average line performance improves by more than 26 pp when the caste composition of the line becomes more homogeneous. These results are driven by assembly lines as opposed to non-assembly production lines where workers are substitutes for each other. Our findings are robust to a host of sensitivity checks, including worker ability, line specific unobservables and line-level trends in production.

Given the absence of explicit group-based incentives, it is puzzling that individual productivity, and especially minimum productivity in the line, improves when teams are more socially connected. In our context, workers receive a fixed, monthly salary but their total earnings depend on their skill grade (with wage differential between grades of about 10-12%) and overtime wages (at higher than regular hourly wage rate). Workers who are more productive have a higher probability being promoted to higher grades or receiving overtime due to recommendations by their line supervisor. Since the line supervisor's remuneration is tied to the line output, there exist *implicit* individual financial incentives linked to higher team production. Thus higher productivity workers have strong incentives to monitor (or mentor) poorly performing co-workers and enforce higher effort from those who are holding up line output.

Our results indicate that monitoring (or mentoring) is more effective when workers belong to the same social networks. Hence if poor performance at work lowers earnings of co-workers in the line due to the production externality, workers are induced to put in greater effort when more of their co-workers in the line belong to their own-caste network to ensure getting network benefits. Our findings can therefore be explained by the social incentives that workers face when their network strength is higher in their production line on a work day. We conjecture that social pressures to increase effort are higher the lower is the initial productivity of the worker, as these workers are most likely to be holding up line output and more likely to need network resources in the future.

Indeed, our worker level data suggest economic interdependence and benefits from one's caste-based networks as sources of information for job openings as well as for referrals. For instance, 75% of the workers obtained information on their current job through their social network while 64% of the informants were employed in the factory at the time of the job opening. Almost a third of these informants were still employed at the time of our survey (conditional on informal flow of information), the majority of whom were line level worker (62%) and/or neighbors (52%) who were known to the respondent for over 7 years. Not only did these social contacts provide information on job openings, 42% of them also referred the worker to the management for jobs. 77% of these workers also say that they would be able to borrow money from this informant in an emergency. Not surprisingly, our results are driven by workers whose job referee is still employed in the factory, validating the claim that possible exclusion from one's social network is a likely mechanism for improved efficiency of same caste workers.

Our accompanying theoretical analysis, therefore, underlines the role of social networks in improving worker productivity in highly competitive product markets, such as the garment industry, where profit maximizing firms are constrained in offering employees explicit monetary incentives.[2] Instead, in such industries firms can leverage social networks amongst workers to relax their constraints on worker compensation, as the insights from the microfinance literature and it's applications in labor economics have shown in different contexts (Varian (1990), Ghatak and Guinnane (1999), Bryan et al. (2015)), Heath (2018), Dhillon et al. (2019)).

Existing research on worker productivity primarily focuses on peer effects as an explanation for variation in worker performance under production functions in which workers are substitutes and effort is observable. Knowledge spillovers or having a more productive co-worker improves worker productivity due to strategic complementarities (Falk and Ichino (2006), Mas and Moretti (2009), Lindquist et al. (2015)). Peer effects on productivity, mediated through social networks that create pressures to conform to a social norm, however, are ambiguous (Bandiera et al. (2010)).[3]

Identity motivations may also impact worker performance. A large literature on lab experiments suggests that team homogeneity leads to more efficient outcomes (Eckel and Grossman (2005), Goette et al. (2006), Charness et al. (2007), Chen and Chen (2011)). Field experiments, however, indicate that the effect of identity on

[2] `https://www.mckinsey.com/business-functions/sustainability/our-insights/style-thats-sustainable-a-new-fast-fashion-formula`; Chang et al. (2016)

[3] Bandiera et al. (2010) find that having a more able, self-reported friend as a co-worker increases productivity of lower ability workers but decreases productivity of higher ability workers in a UK based soft fruit producing firm.

worker performance is contingent on the nature of financial incentives (Hjort (2014), Kato and Shu (2016)).[4]

Almost all of the literature we cite above focuses on workers as substitutes in the production process,[5] and on peer effects such as conformism or strategic complementarities through knowledge spillovers. However, the case of workers who are complementary in production, thus creating financial spillovers, has not been examined. The only paper we are aware of that focuses on complementarity in production, and assembly lines in particular, is a lab-in-the field experiment with garment factory workers in India. Afridi et al. (2020) identify pro-social motivations between socially connected co-workers as a determinant of higher group output and better coordination. Our research, thus, extends the broader literature on the role of social networks in job search to its impact on worker and firm productivity.

Our findings speak to multiple strands of literature on worker incentives as well as to the existing research on management practices and firm behavior. We identify pre-existing social connections in the form of caste-based networks, amongst workers as another channel through which economically interdependent workers can influence each other's performance and thereby affect the group output. Even though our analysis is based on garment factory production lines, it is applicable to situations where the production process is organised into teams with fixed, individual wages. It suggests that social connections amongst workers can incentivize them to be more productive for improving individual or group productivity. The results of our analysis indicate that identifying workers who are widely connected to co-workers through job

[4]Hjort (2014) finds that ethnic homogeneity can lead to higher team output as compared to heterogeneous teams at a flower processing plant in Kenya, where workers are both substitutes and complements in the production process, and when payoffs are based on individual output. Shifting from fixed pay to performance pay based on group output, however, reduces allocative inefficiencies in multi-ethnic teams. In contrast, however, Kato and Shu (2016) show that migrant social identities mitigate competition among in-group members thereby reducing productivity in homogeneous groups when wages are relative, in a cloth manufacturing firm in China.

[5]Hjort (2014), discussed above, is an exception.

referrals or residential location could carry implications for productivity through the optimal design of production schedules and composition of teams in the firm.

The remainder of the paper is organized as follows. Section (2) describes the background of our study, including the production process and worker incentives in garment factories. Section (3) summarizes the observed data regularities. Section (4) provides the theoretical framework. We discuss our empirical methodology, report the results of our analysis in Section (5) and conduct robustness checks in Section (6). We underscore the mechanism that explains our findings in Section (7) and conclude in Section (8).

2 Background

2.1 Caste as a proxy for social networks

Workers' social networks play a significant role in the functioning of labor markets (Afridi et al. (2015)) and in ensuring migrants' economic mobility, more so in low income countries (Munshi (2014), Munshi (2019)). Historical data highlight the salience of social networks based on caste and homophily in India (Munshi (2019)).[6] Chandavarkar (1994) documents historical migration to industrial hubs within the framework of caste, kinship and village connections from India's rural areas. The rural migrants not only resided with their co-villagers, caste-fellows and relatives in the city but also obtained work with their assistance (Burnett-Hurst (1925), Gokhale (1957)). Today caste and kinship continue to be integral to individuals social networks in urban areas, particularly amongst rural migrants in the city's working-class neighborhoods.[7]

[6] Caste, a unique feature of Indian society, is inherited at birth. The caste system classifies Hindu society into four hierarchical occupational groups or *varnas* - *Brahmins* (priests and scholars), *Kshatriyas* (warriors and rulers), *Vaishyas* (merchant class), and *Shudras* (cultivators). Those engaged in menial tasks, such as scavenging, are considered to be outside the varna system and untouchable.

[7] 30% of the Indian population has migrated from another part of the country at some point, of which almost 15% migrate for employment (GOI (2011)).

In our study we focus on India's garment manufacturing sector, which is amongst the largest providers of employment for low skilled workers offering work opportunities to rural migrants from diverse caste groups. Migrants tend to find employment through information about job openings and referrals from their caste-based networks, and may also depend on their support to weather socio-economic shocks and for risk-sharing. In our data we find that a majority (74.5%) of the garment factory workers obtained information about job openings through their network. Conditional on the informant being still employed in the same factory as our survey respondent, 42% of workers were referred to the management by the informant, who was most likely a co-worker in the same production team or line (61.6%) and/or a neighbor (52.1%) whom they knew for some time (7.4 years).

While our data suggest that the job informants typically live close to or within the worker's residential units or migrant colonies, they often belong to the same caste groups as well.[8] Of the workers residing in the same town in our sample, 53.5% shared the same caste category. Residential segregation by caste becomes stronger as we move from towns to clusters, colonies and lanes (63.2%, 66.3% and 83.2%, respectively, belonged to the same caste category, conditional on both caste and current residence information being available for a worker in our data). Thus, own-caste neighborhoods represent the social networks that workers derive economic benefits from.

2.2 Garment production and worker incentives

The manufacturing process in a garment factory encompasses multiple departments. We focus on the production department, responsible for the stitching of garments. A

[8] While Vithayathil and Singh (2012) show high levels of residential segregation by caste at the ward level in the large metropolitan cities in contemporary India, higher than segregation by socio-economic status, Bharathi et al. (2019) find that at the census enumeration block level (smaller than a ward, with about 100-125 households) there is an even higher degree of residential segregation by caste categories.

single factory can have multiple production or stitching floors. On each floor there are multiple production lines in which stitching machines placed one behind the other are operated by workers (see Figure A1 in Appendix A).[9] Each line is assigned a particular style of garment to be produced over certain days until the production target for that garment-style is met.

There are two types of production lines: assembly and non-assembly. In an assembly line each worker contributes to the production of the garment by performing different assigned operations. She receives bundles containing cut pieces of parts of a garment at the beginning of every work hour. The production process is, thus, simultaneous and complementary. The stitched garment is then assembled at the front of the line.[10] Hence there exist strong production externalities in the assembly line - the total number of finished garments produced by the line on a day would depend on the productivity of the least efficient worker.[11]

Observability of co-worker effort is imperfect due to differences in operations performed by workers in an assembly line. However, as can be seen from Figure A1, workers can see who is sitting in their line even though they cannot directly observe each other's output. Moreover, workers would be aware of where production bottlenecks exist. On the other hand, in the less ubiquitous non-assembly lines the entire line is responsible for producing only one part of the garment, e.g. collars. Thus, all workers perform the same operation.

The management monitors workers' performance via production line supervisors.

[9] Besides the machine operator, who is responsible for stitching, the production line includes helpers who assist with specific operations (fold, cut, match or iron parts of garments) - about 16% of workers in a line on a day. We use the term 'worker' to denote both operators and helpers.

[10] Figure A2, Appendix A, illustrates the general production process for a shirt in an assembly line, for instance. While some workers perform different operations on collars (e.g. stitching, hemming), other workers may be responsible for operations on sleeves (e.g. attaching cuffs, stitching armholes) and so on.

[11] Our claim is validated by a significant, positive correlation between the line level output recorded by the factory management and the output of the least efficient worker in that line in our data.

It is the supervisor's responsibility to ensure that the line meets its production targets for the work day. His financial incentives - bonus and promotions - are hence linked to his line's performance, as per our discussion with the factory management. Supervisors receive a monthly bonus if their line's efficiency (averaged across workdays) in that month crosses a threshold, with a higher bonus at higher threshold.[12] Although workers receive a fixed, minimum wage paid as a monthly salary, there are different grades of workers classified according to skill measured through a performance test on entry and based on past experience and training they have received. The wage differential between grades is about 10-12%. During the period of our study workers were not offered any performance linked bonuses.

Worker's chances of being promoted to higher grades (with higher salary) improves with supervisor goodwill, which itself is linked to line productivity. Since the management maintains records of operational efficiency at the line level, supervisors are aware of which worker-operations are holding up the line output. Data suggest that an overwhelming majority (almost 84%) of recommendations for worker promotions in the factory are from the same line as the recommending supervisor. The correlation between recommendations of promotion and the skill-designation of workers is statistically significant (0.52, $p<0.01$). The workers recommended for promotion by the production floor manager (higher-up management) are also recommended by their supervisors, and the correlation between the type of recommendation by supervisor and floor manager is significant (0.50, $p<0.01$).[13] Supervisors also allot limited overtime positions to workers, which typically pay an hourly wage higher than minimum

[12] Supervisors receive a fixed monthly salary which is higher than the workers' salary. If the supervisors' line achieves >=80% efficiency then the supervisor receives a lump sum bonus of Rs. 3000 in that month, for 80% to 75% a bonus of Rs. 2000 and for 75% to 70% line efficiency a bonus of Rs. 1800, and so on. Thus the bonus is a substantive 8-14% of monthly earnings, given supervisor salary of about Rs. 22,000 per month.

[13] The data (N=431) consist of all independent recommendations from supervisors and floor managers of the production department for different types of promotions and a random sample of non-recommended workers (approx. 15% of workers per line) from one of our sampled factories.

wages. Workers total earnings, therefore, depend not only on their fixed grade pay but also overtime wages. Since overtime positions are few, more productive workers have a higher probability of receiving over time work. In essence, therefore, there exist implicit individual financial incentives linked to being a more productive worker in a line. Given the production externalities in the assembly line, the performance of co-workers in an assembly line can therefore impact the earnings of a worker.

Our identification strategy, discussed in detail later, relies on unanticipated worker absenteeism leading to arguably exogenous changes in the daily composition of production lines. Given the constrained supply of skilled workers and the high proportion of migrant laborers in this industry, worker attrition and absenteeism is significant (GOI (2018)).[14] The number of observed workers in a line on a workday deviates and varies day-to-day from the allocated line strength - an average daily deviation of 31%. This implies an average change in line strength of over 15 workers per day. Although most of this variation in manpower can be on account of changes in production targets, it does not account fully for daily variation. While supervisors may reassign workers within their lines, workers can also be moved across lines to address attrition and absenteeism to meet production targets. Any reassignment of workers across the lines is controlled by floor or line in-charge according to the supply and demand of workers, the relevant skill requirement and production deadlines.[15] Thus, the daily composition of a line can vary both due to worker absenteeism as well as any worker reallocation thereof. We discuss this in more detail in the following section.

[14] Average reported weekly absenteeism is about 10% in our sample, but is likely an underestimate. Workers switch jobs frequently in the garment industry. A typical worker in our sample was employed in the current job for 2 years but had been in the garment industry for almost 4 years. Poaching of workers is common, especially during the peak demand season. Even during our survey period, which was a normal production period, more than 8% workers exited while over 5% joined the factory.

[15] Adhvaryu et al. (2019) document limited relational trading between supervisors inside garment factories to reallocate workers in order to address worker absenteeism.

3 Data

Our data come from two factories located in the industrial hubs of Faridabad and Gurugram (both in the National Capital Region, NCR) in the state of Haryana, India. While the former factory caters to foreign buyers, the latter manufactures garments for the domestic market. 89% of our sample of workers belong to the exporting firm which was significantly larger. We construct our dataset from two main sources: (1) own survey of factory workers and (2) administrative data from the factory management.

3.1 Survey data

We conducted a census of workers employed in the two factories during a regular production season in August - October 2015 (approximately 61 continuous work days) to obtain information on their demographic and other individual characteristics. The resulting data on 1916 workers and 73 supervisors include all workers and supervisors in the stitching department of the sampled factories.[16] The survey gathered information on individual characteristics, including native state of residence and caste, years of experience in the garment industry, and the process of obtaining the current job particularly referrals. We also conducted a shorter survey of supervisor characteristics.

Using each state government's administrative list of Scheduled Castes (SC), Scheduled Tribes (ST) and Other Backward Castes (OBC) and the native state reported by the worker (or supervisor), we mapped the reported sub-caste or *jati* of each worker (supervisor) into 3 categories: (1) **L** i.e. SC or ST, (2) **M** i.e. OBC and (3) **H** or high castes who do not benefit from affirmative action policies. Note that we view broad caste categories as suitable proxy for networks - relevant for residential decisions (e.g.

[16] Since worker attrition is high in this sector, we kept in touch with the Human Resource (HR) department to ensure that any new worker recruited during our study period was included in our survey.

areas are often classified as *harijan* or low caste) or in fostering shared experiences. Narrow caste categories, viz. *jati*, on the other hand, represent identity concerns, which is not the focus of this paper.

3.2 Worker productivity and attendance data

The factory managements were recording hourly, line level productivity by worker-operation within a line. For the purposes of our study the management agreed to also record the unique ID of each worker. This allowed us to obtain disaggregated worker level output, and also follow workers across lines and work days. These data were obtained for a period of 31 (continuous) working days between September-October 2015, a sub-set of the 61 days during which the worker census was conducted.[17]

One obvious challenge in comparing worker productivity is the difference in the operations they perform. However, each style-operation combination has a specific daily target output associated with it which is set by the industrial engineer of the factory. This is calculated using the SAM (standard allowable minutes) based on a standardized global database that includes information on the universe of garment-styles.[18] Dividing the recorded total daily output (summed over 8 hours in a work day) by the target daily output according to the SAM per worker-operation, we end up with a normalised measure of worker productivity for each style-operation. Thus, the closer the worker's actual output is to the target output, the more efficient or productive is the worker.[19] Each worker's efficiency, therefore, is measured as follows:

[17]Every production line has a 'feeder' who notes down productivity by operation in a line each hour. For our study period the 'feeder' also recorded the name and unique ID of the worker at each operation in the line.

[18]The SAM is the time it takes in minutes to conduct a particular operation under ideal conditions. It is, thus, higher for more complex operations. Using the SAM for the style-operation, we can calculate the target output per worker per style operation. The presence of sufficient Work-in-Progress (WIP) pieces ensures that individual worker productivity can be measured by SAM.

[19]After normalization, about 1.2% of person days had efficiency>1 (mapping into 149 workers). t-test shows that these 149 workers have significantly higher efficiency on other working days as well. We keep these observation in our analysis and approximate their efficiency to 1.

Daily worker efficiency = Daily output of worker/Daily target output of worker

We measure line level performance in two ways. First, as the average efficiency of all workers in a line on a day and second, as the efficiency of the least efficient worker since the lowest effort determines the total output (or units of complete garment) in the assembly line. Data on workers' and supervisors' daily attendance was obtained from the Human Resource (HR) departments of the two factories.[20] We match workers across the survey, production and attendance data using unique worker IDs to obtain a panel of 1916 workers. Taking into account missing information across the three data sources, our final dataset consists of 1744 workers and 34,641 worker-days.[21]

Table 1, column 1, summarizes the characteristics of our sample. More than 66% of the factory workers are migrants from two large north-Indian states of U.P. and Bihar. On average, a worker has been in the garment sector for over 3.5 years and 74.5% of them obtained their current job through information from their social network. Conditional on the job informant being still employed at the factory, 42.1% of workers were referred to the job by the informant. In contrast to the pervasiveness of job network of workers, on average, a worker reports having less than 2 friends in the factory.[22] The same worker characteristics are described by their caste category in columns 2-4 in Table 1. The largest proportion of workers belong to the H caste category (47%) followed by M (31%) and L caste categories(22%), in our sample. The

[20]Workers reported their unique IDs in the survey data which were cross checked using the HR data. In the export factory a card punching system was used for recording attendance. In the domestic factory, workers were required to submit their ID cards to the HR representative who would then enter their unique IDs into the computer records at the beginning of the work day.

[21]We do not have production data for 112 surveyed workers who exited the factory before we started collecting the output data. 6 workers for whom we have HR records are missing from the production data. Information on native state or *jati* or both is missing for 52 workers. We drop 2 workers for whom we have only half-day attendance information. In total, therefore, we lose 172 workers from our original sample of 1916. We do not find any significant differences in the characteristics of workers who attrited from our sample and those who were on the rolls during the collection of the production data. See Table A.1 in the Appendix A for details.

[22]Majority of supervisors were from M category unlike workers who were more likely to belong to H category. Almost 35% of workers belong to the same caste category as their line supervisor. We do not find any impact of caste alignment of supervisor and worker on latter's productivity.

characteristics of workers are largely similar across caste categories - in particular we find no evidence of systematic productivity differences between workers of different caste groups.[23]

Table 2, Panel A, shows the average efficiency of a worker and across worker-days on the stitching floor. Workers typically achieve only around 31% of their target output, on average. Worker efficiency is not statistically significantly different across caste categories. The average network strength or "proportion own caste", measured by the number of workers belonging to the caste category of the worker divided by the total number of workers in the line on a workday, is 39.5%. Panel B shows the performance of a line across the sampled period. The average efficiency of a line is about 30% and the average minimum efficiency of line is just over 5%, indicating that least performing worker is meeting only 5% of the target output. We find similar productivity statistics by line-days. The network strength in Panel B is measured by the sum of square of the shares of each caste category in a line on a day.

Figure 1 exhibits the variation in the line performance cross-sectionally, averaged across work days, in terms of minimum efficiency (left panel) and average efficiency (right panel). While the mean minimum efficiency across lines varies from 2% to over 15%, the average efficiency, though higher, exhibits greater variance (16 - 44%). The variation in performance across production lines is accompanied by wide variation in both the strength (number of workers) of a line (Figure 2a) and its performance across workdays (Figure 2b). Figure 2a shows the number of workers in a representative line and the day-to-day variation in its strength. The absolute deviation of the observed strength from average strength of the line is between 0 - 39% during our sample period.

[23] The p-values for each pairwise t-tests of efficiency varies from 0.06 to 0.37. Using the median worker efficiency calculated for workers observed number of days, we further divide workers into low (those below median) and high ability (equal to or above median) and run a probit model regressing ability type on worker characteristics. The coefficients on caste group (L being the benchmark category) are insignificant, thus, validating the claim that productivity is not systematically correlated with caste groups.

The average absolute deviation in line strength from the previous day is about 16%. Note that the daily changes in the number of workers in line underestimates changes in line composition since workers are also reallocated across lines.

Figure 2b traces the average efficiency of a line across workdays, which can be seen to vary by more than 25 percentage points (pp). Thus average performance of a line may hide much higher variation in performance across workdays within the same line. The proportion of L, M and H category workers in the line as shown in Figure 2b varies along with changes in line strength and efficiency. The proportion of workers of each caste category in a line across work days can vary by up to 22, 12 and 18 pp for the H, M and L caste categories, respectively.[24] As discussed in the next section, neither worker productivity nor absenteeism rates differ significantly across caste groups in our sample.[25]

We correlate the caste composition of the assembly line, worker and line level productivity in Figure 3 to show that the higher the proportion of own caste workers in the line (Figure 3a) and the more homogeneous the caste composition of the line on a work day (Figure 3b), the higher the efficiency of the worker and the minimum efficiency of the line on that day. This suggests that social networks amongst co-workers, mediated through caste, may have a significant impact on individual and group productivity.

4 Theoretical Framework

We build on the insights from the microfinance literature (Varian (1990), Ghatak and Guinnane (1999), Bryan et al. (2015)) and applications in labor economics (Heath (2018), Dhillon et al. (2019)) to theoretically demonstrate how social networks can

[24]The caste composition of the Indian population is 28.2% SC or ST, 41.1% OBC and 30.8% high castes (Census 2011).

[25]Since workers in our study come from approximately 300 districts across 16 states, the likelihood of workers of same *jati* sitting in a particular line on a day is negligible.

solve moral hazard/adverse selection problems when formal institutions cannot, in a context where workers are complementary in the production process. Below we provide a sketch of the model and the intuition for the results. The details of the model are available in Appendix B.

When worker effort is imperfectly observed, wages are fixed, and punishment is limited (minimum wage constraints), the firm faces a moral hazard problem - workers have low incentives to put in high effort. On the one hand, the product market is highly competitive constraining the firm's ability to use high powered incentives, while on the other, workers who are paid close to minimum wages can get jobs easily at other factories at the same low wages, constraining the firm's ability to punish workers.

Our model shows that in a context where paying all workers individual incentives to put in high effort is too expensive for the firm given the high cost of effort for low ability workers and the limited options to punish workers for poor performance, the firm provides team incentives via the supervisor. As discussed previously, the supervisor's incentives are linked to line performance and they influence workers' receipt of overtime and promotions. High ability workers are more likely to get overtime and promotion in general, but particularly when *line* output is high, as it generates goodwill from the supervisor. Together with complementarity in production, this implies that high ability workers have incentives to punish low ability workers or shirkers who are holding up line output to put in more effort by monitoring/mentoring them.[26]

It is not always feasible for high ability workers to push the low ability workers – however, when social networks in the line are salient they can do that through network reputational rewards and punishments to low ability workers (in similar ways to the microfinance literature). The workers' caste and residential clusters are closely knit

[26]We use the two terms - monitor and mentor - interchangeably, henceforth.

making the threat of social sanctions credible. Being in the same network confers an advantage in terms of being able to promise future rewards or punishments outside the firm.

Formally, suppose there are two workers in the line (the model is easily generalized to more workers) characterized by their observable ability types $\theta_i \in \{\bar{\theta}, \underline{\theta}\}$.[27] Output of worker i is increasing in θ and effort. For simplicity we assume the production function for worker i is given by $y_i = \theta_i + X$, where X is a random variable that takes one of the values $\{x_1, x_2\}$ with $x_1 > x_2$. The production function therefore has an individual component θ_i and a joint component, X which depends on the profile of efforts by the two workers. We assume model parameters that capture complementarity of effort between the two workers. Average line output is the minimum of the y_i, capturing the constraint that the low ability worker puts on increasing line output. A line can have workers of different productivity: in our model we can have either both high ability, both low ability or one low and one high ability worker. Line output is highest when workers are high ability and put in high effort.

First, we show (see Appendix B) that if minimum worker's ability on the line ($\underline{\theta}$) is very low, then it may not be possible to induce high effort from the low ability worker in the absence of social networks. The expected overtime and promotions needed to incentivize the worker is too costly relative to the gain in line output. Therefore the solution might be either that only high ability workers put in high effort or none of the types do. As a result, line output is low and high productivity workers have low expected wages.

In order to capture the effect of networks, we introduce an exogenous probability of separation from the firm $1-\gamma(\theta)$, which is higher for low ability workers, $\gamma(\underline{\theta}) < \gamma(\bar{\theta})$,

[27]Usually workers in an assembly line are of different grades, based on their efficiency levels.

as chances of being fired are higher even for the same effort levels.[28] Separated workers rely on their social networks, in particular on more experienced workers for getting other jobs via referrals or for helping over a financially difficult period. Conditional on separation, a worker will enjoy utility from the network denoted as $V(f_i^k|e_i)$ where f_i^k is the number (or fraction) of coworkers in the social network of worker i of caste k in the line and e_i is the effort choice of the worker. When monitoring is feasible then V can be conditioned on effort of worker i (in our setting, low output workers who are holding up line output are often called out by the supervisor- this observability is all that is needed for the model). $V(\cdot)$ is increasing in f_i^k: the higher the number of co-workers from one's social network, the higher is V, because co-workers of the same network are likely to observe worker i if called out for holding up the line by supervisor, live close to worker i and have links with other network members who can help/ostracize the worker, and may themselves not provide referrals to the worker in future. The larger the strength of the network on the line or in the factory, the better is information transmission on worker i to others in the network but outside the line/factory. We assume that the share of other out group or out of network peers in the line does not affect workers (we have checked that this assumption holds).

Assume that monitoring by high ability workers is profitable, (i.e. the marginal gain in wages if joint production is higher than the marginal cost of monitoring) then (a) high ability workers benefit from monitoring low ability workers as they get a higher expected wage when line output is higher, and (b) low ability workers have network related incentives to put in high effort despite having low expected wages in the firm. Therefore $V(f_i^k|e)$ is a network based incentive to put in high effort.

Our main conclusions, therefore, are as follows. First, when $\theta_i \neq \theta_j$, i.e. the line

[28]Adding this in the benchmark case without networks would not change our results - the key point is the ability to reward or punish workers in the same network.

has heterogeneous ability types, monitoring costs are low, and $\underline{\theta}$ is very low, then both workers increase effort when the share of own network increases in the line. When $\underline{\theta}$ is in an intermediate range then only the low ability worker increases effort. When $\underline{\theta}$ is sufficiently high, then neither of the workers increases effort when share of own caste workers increases. Overall, the range of parameters for which low ability workers increase effort when the share of own caste workers increases is larger than for high ability workers implying that responsiveness of low ability workers is higher than high ability workers. Second, when ability composition within the network is more homogeneous then the effects on effort will be lower. Thus, when there are highly productive workers in the line coupled with some low productivity workers we should observe larger effects on average and minimum productivity within the network. The reason for the second result is that only high productivity workers have incentives to monitor other workers as their monetary gains are larger. Moreover if there are mostly high productivity workers in the line, there is no need for networks to improve line productivity.

5 Methodology and Results

5.1 Identification

If workers self-select or are sorted into production lines by caste, then any relationship between worker efficiency and composition of a line may be endogenous. As discussed previously, the management allocates workers to lines when they join the factory. We observe a significant difference in the allocated and observed line strength across work days. Daily changes in line strength leads to changes in the worker composition of the line due to unanticipated worker absenteeism and attrition, which is higher than the average in the manufacturing sector. In addition the floor manager has to re-allocate workers across lines due to worker absence so as to meet production targets. Given the high pressure to meet production targets (due to high competition in the product market), the scope for being able to selectively choose workers is limited.[29]

To test our claim that the caste of a worker and the worker's observed line on a work day are independent we follow Hjort (2014) in conducting the Pearson's chi-square test. Specifically, if $P(C_i)$ denotes the probability of worker i belonging to the caste category C, and $P(L_i)$ denotes the probability of worker i being observed in line L, then $P(C_i \cap L_i)$ is the joint probability of worker in caste C sitting in line L. If the two events are truly independent then we should find that $P(C_i \cap L_i) = P(C_i) \cap P(L_i)$ holds on average. From the production data we have information on the caste composition of each line on a day, $P(C_i \cap L_i)$, and on $P(L_i)$. We perform this test for each line and each work day for both the factories in our sample. Table A.2 in Appendix A gives a snapshot of the caste distribution of workers in production lines on a randomly selected work day for the export factory and Table A.3 shows the same analysis for the domestic factory. We fail to reject the null hypothesis at 5% level of significance for all 1043 line days, except 2 (3) work days in the export (domestic) factory.

Moreover, we find that worker absenteeism is not systematically correlated with workers' caste category (Table A.4, columns 1-2 in Appendix A). In addition, there is no correlation between the average number of lines a worker is observed in and her caste in our production data. Thus both worker absenteeism and reallocation are independent of own caste. Further, we do not find a systematic relationship between either a line's daily or lagged production target and its caste concentration on a work day (Table A.4, columns 3-4 in Appendix A), indicating that supervisors do

[29]We deliberately emphasise the use of caste as a proxy for networks. Given the politically sensitive nature of such classifications and the possibilities of conflict among workers, it is unlikely that the factory would group workers according to caste. In our sample the management did not collect information on workers' caste at the time of recruitment.

not strategically adjust line caste composition in response to productivity targets. In our empirical analysis, therefore, we use worker absenteeism as a source of exogenous variation in the caste composition of workers in a line across days.

5.2 Estimation methodology

Our baseline specification exploits the panel structure of our data and is given by:

$$\mathrm{Y}_{ilt} = \alpha + \beta network\_strength_{ilt} + \gamma \mathrm{X}_i + \epsilon_{ilt} \tag{1}$$

where, Y_{ilt} is the efficiency of *i-th* worker sitting in the *l-th* line on *t-th* work day, $network\_strength_{ilt}$ is defined as the number of workers belonging to *i-th* workers caste category (H, M or L) divided by the total number of workers in the line on that work day. It reflects the strength of caste based social connections a worker can have in a line on a given day. $\mathbf{X_i}$ is a vector of worker characteristics such as caste category, age, marital status, religion, native state, experience, education and number of reported friends in the factory. Throughout, we control for the number of workers in the line on a workday. Standard errors are clustered at the factory-line level. β is our main coefficient of interest. If β >0 then it would suggest that having more workers of one's own caste category in the line has a positive effect on worker's productivity.

Equation (1) ignores unobserved, time invariant individual heterogeneity, such as ability, which may be correlated with the line's caste composition and also affect individual productivity. We, therefore, include individual fixed effects (FE) in subsequent specifications, besides factory floor and line FE to account for floor and line level unobservables (e.g. floor managers' and line supervisors' characteristics).[30]

[30]Suppose worker motivation to work on date t is affected by caste composition in line l on day t, then it may be argued that absenteeism (and hence caste composition) in line l on day $t+1$ is affected by caste composition on day t. But we have already shown that assignment of workers is independent of caste and

To analyze line level productivity we estimate equation (1) at the line level and measure social connections amongst workers in the line by the caste concentration index (CCI) which is the sum of the square of proportion of each of the three caste categories in a line on a day. The higher the caste concentration index of a line the higher would be the caste homogeneity in that line. Hence workers in that line are more likely to belong to the same social network and be more connected. We also include the average worker level characteristics in the line, included in vector $\mathbf{X_i}$ in equation (1), and the strength of the line on each workday as controls. In subsequent, stricter specifications, we include floor and line FE to control for time invariant, line level unobservables.[31] The standard errors are clustered at factory-line level, as in the individual level analysis.

5.3 Results

5.3.1 Line composition and worker performance

The results of the analysis using equation (1) are presented in Table 3. In the top panel the sample consists of all production lines - assembly and non-assembly. Column 1 shows estimates of equation (1), where 'Network strength' is as defined in equation (1). The coefficient β is positive, suggesting that a 1 pp increase in the proportion of workers of one's own caste increases an individual worker's efficiency by 13.7 pp. In column 2 we include individual FE. The coefficient of interest remains significant at 1% level, and is comparable in magnitude. In subsequent columns we include floor (column 3) and line (column 4) FE. The magnitude and significance of the estimate

absenteeism does not vary systematically by caste. If motivation of workers is indeed affected by caste composition, then note that since on average the largest worker group is H type, we would expect minority caste groups, M and L, to be disproportionately more affected by caste composition of their line. However, despite the asymmetry in the share of castes of H vs. M and L in the workforce, we do not find a significant difference in the absenteeism rates for the three castes.

[31] We find that line level productivity and absenteeism are not systematically correlated when we regress the dummy $Y = 1$ if average efficiency of the line $\geq$ median average efficiency across line-days on average line-day absenteeism in a probit model.

is robust.

As discussed previously, we do not find a correlation between trends in line characteristics that affect productivity and its caste composition. Nevertheless we account for variation in output targets due to changes in production styles that may be correlated with both line composition and worker performance. On average, we observe 2.8 unique production styles per line over the 31 day sample period. Hence one production style runs for over 10 days in a line. Thus in column 5 we include secular trends through work week FE and line specific work week trends. β remains significantly positive, suggesting an 8.9 pp increase in worker productivity for every pp rise in share of own caste workers in the line. Our results are unchanged when we account for secular work day trends in column 6 along with individual and line FE.[32]

Since the production procedure followed in assembly lines is subject to productivity spillovers unlike non-assembly lines, we separate the sample of assembly lines where each worker performs a different operation in the line in the bottom panel of Table 3. The coefficient β is comparable, suggesting 9.8 to 19.5 pp higher worker efficiency when the proportion of own caste workers in the line rises by 1 pp. This suggests that the overall effects we observe in columns 1-6 are driven by assembly lines.

To elaborate on what the estimates imply, recall that workers receive bundles of cut sub-parts of a garment at the beginning of the each work hour. Now suppose a worker receives 4 bundles of 20 pieces each, and her hourly target output is 80 stitched pieces while her daily target is 640 pieces (8 hours x 80 pieces). Given the average efficiency of 31%, assume she manages to complete only 192 pieces. An increase of 10 pp in her daily efficiency implies that her daily output increases by 64 pieces or, on

[32] Note that since we identify the effect of network strength through line-day variations, we cannot include line specific work day FE along with line and individual FE.

average, 8 additional stitched pieces per hour when the number of own caste workers increases by about one-half (i.e. about 1 pp in an average line of 33 workers with equally distributed H, M and L caste.). Since the mean worker efficiency is 31% the most conservative estimate in column 5 suggests that worker efficiency can rise by approximately 28.7 - 31.6% when a worker is more socially connected within her line.

5.3.2 Line composition and line performance

In Table 4 we estimate the minimum line efficiency using equation (1) for all lines (Panel A) and only assembly lines (Panel B). In Table 4, column 1 we include only line level characteristics as controls and subsequently augment the specification with factory floor (column 2), line (column 3), week and line specific work week FE (column 4) and work day FE (column 5). A one pp increase in the network strength as measured by the CCI causes a 10.5 pp (column 2) to 16.8 pp (column 4) increase in the line's minimum efficiency in the full sample. Restricting the sample to assembly lines alone, the sample size falls from 1043 to 868 but does not change our estimates much. Given that the average minimum line efficiency is 5%, the estimates of the impact of network strength are very large. In the strictest specification with line specific weekly trends, the results suggest that the minimum efficiency of the line or the least productive workers performance increases by 280-336% when more workers in the line belong to the same caste-based social network.

In Table 5 we show the results of the same analysis but when the dependent variable is the average efficiency of the line. Columns 1-5 indicate a 25.6 to 39.8 pp improvement in a lines average efficiency when the caste composition of the line is more homogeneous in Panel A. We restrict the sample to only assembly lines and redo the analysis in Panel B. The point estimates are similar to those shown in the top panel. Our preferred specification with line specific weekly trends suggests 88.3 -

108.7% higher average efficiency when the lines network strength increases by 1 pp, given mean average line efficiency of 30%.

Overall, and in line with the theoretical model, our results suggest that the higher the proportion of co-workers from the same caste in a line on a day the higher is the performance of the worker and the line.[33] The estimated effect sizes are plausible since the supervisor's bonus increases non-linearly with higher line efficiency thresholds as discussed in Section 3. In percentage terms, given the low minimum efficiency of 5%, we observe a larger impact of network strength on the least productive workers in a line.

6 Robustness

6.1 Sample selection

A simple t-test for those workers who have lower vis-à-vis higher than median attendance shows that the former have significantly lower efficiency. Even though we find no statistical difference in workers' performance by caste, results can be biased if absenteeism or the probability that a worker is observed in the data is systematically correlated with worker productivity or ability. Using the daily attendance data from the HR records for 61 working days (1^{st} August to 14^{th} October 2015) and worker production days data from the stitching department for 31 days (8^{th} September to 14^{th} October 2015), we analyze the characteristics of workers who are observed more regularly. As shown in Table A.4, there is no systematic relationship between caste category and worker presence, but experienced workers are more likely to be observed working.[34]

[33] We do not find any non-linear impacts of network strength on either individual or line level performance.

[34] Unbalanced panel at the line level can be an issue if the caste composition differs systematically across lines which are observed less versus those that are observed more often. However, the t-test suggests that the caste concentration across days doesn't differ significantly for assembly lines which are observed more versus those observed less than the median number of working days.

Suppose, however, that more productive workers replace the less productive, absent workers in a line on a day. If this is systematically correlated with the caste composition of co-workers in a line our results above would be biased upwards. We adopt a non-parametric method to check the robustness of our results in Table 6 to this potential selection bias - inverse probability weights (IPW) suggested by Moffitt et al. (1999) and Baulch and Quisumbing (2011). Intuitively, IPW method gives greater weightage to workers who are more likely to be absent (and of lower productivity) on a given work day.[35]

Using the inverse of predicted probability of being present, we re-run the worker level analysis in Table 6. Columns 1-5 report the original, unweighted estimates while columns 6-10 show the IPW estimates for corresponding specifications. We do not find any significant difference either in the magnitude or significance of the estimates, suggesting that selection on worker characteristics is not driving our results.

6.2 Trends

As we mentioned previously, demand can vary over time both within and across lines in a garment factory. This can influence individual and line productivity, as well as the composition of workers in a line. Supervisors and managers may reallocate workers across or within lines purposively to meet production targets which may be correlated with caste categories of workers. Note that line productivity is measured at the workday level which does not allow us to control for line specific workday FE in the line level analysis. However, in addition to line-work week FE reported in Table 3, we include line specific garment style FE in Table A.5. Since we have data

[35]First, we regress worker attendance (=1 if present and 0 otherwise) on worker characteristics (age, secondary level or higher education, married, female, Hindu, native state (Bihar), caste dummies, experience in garment manufacturing (in years), used social ties for obtaining job information for the current job, reported number of friends in the current factory and reported line strength) to predict the probability of the worker being present on a workday. We then use the inverse of the predicted probability of each worker's attendance from this probit model to weight our main estimating equation).

on production styles only for the large export oriented factory, we restrict our sample to assembly lines in this factory. Our estimates remain significant and comparable to those reported in Table 3.

In Table A.6 we also report the results for line performance analysis with line level-garment style FE, since production styles can affect line characteristics, targets and productivity. Our results are robust to secular and line specific trends throughout.

6.3 Number of clusters

Since changes in line characteristics can occur at daily level, we alternatively cluster our standard errors at line-day level in Table 7. Our estimates are significant at 1%. We, however, contend that clustering at the higher level of aggregation - the line - as in all our results above, is more accurate.

However, a concern with our estimates in Tables 3-5 is that high intra-cluster correlation, coupled with the small number of clusters (production lines) in our study, would lead to incorrect standard errors. Even though the number of clusters (or lines) do not fall below the acceptable standard of 30, we may be falsely inferring the significance of the coefficients. We, therefore, report our results with bootstrapped standard errors in Table A.7. Columns 1-4 report the results for the individual level analysis while columns 5-12 show the line level analysis.[36] Our standard errors are marginally higher but the main coefficient of interest remains significant, consistent with results reported in Tables 3-5.[37]

[36] We show pair-wise bootstrapped standard errors, with (col 1) and without clustering at the line level (col 2-4, 5 and 9), respectively. We report wild-cluster bootstrapped standard errors (Cameron et al. (2008)) in columns 6-8 and 10-12. Please see table notes for explanation of choice of bootstrap procedures.

[37] We also drop outlier observations, i.e. line-days on which worker strength falls in the lowest one percentile of the distribution of strength and work days on which the number of factory lines is less than 30. In this sample of 944 line-days we wild-cluster bootstrap the standard errors. Our results are qualitatively similar to Tables 4 and 5.

7 Mechanism

In this section we provide some additional supporting evidence for the mechanism we propose. Our theoretical framework relies on the ability of social networks to provide reciprocal benefits when workers help their peers to get overtime or promotions. Commitment to the network is typically imposed through threats of exclusion from the network and/or social sanctions to deter deviations from cooperation or equivalently, rewards from cooperation (Munshi (2014)). If own-caste workers reside close to each other and depend on each other for information on jobs, referrals or financial help, these threats become credible. The description of job informant characteristics in Table 8 (Panel A), based on our worker survey data, suggests that job informants are residential neighbors and may also be co-workers in the production line. Table 8, Panel B shows that there is significant residential segregation by caste - the proportion of workers who belong to the same caste and town/cluster/colony/lane is high and increasing as the residential unit is defined more narrowly. 83.2% of workers who reside in the same lane in a colony also belong to the same caste category in our data. Consequently, the higher the own caste-proportion in the line on a day, the higher is the share of workers who co-reside, as shown in Panel C of Table 8, and the higher the chances of information on worker performance to network members and on jobs coming from co-workers/network members.

Naturally, when there are more members of a worker's caste in a line, slacking can be more costly if it adversely affects the productivity of own-caste co-workers in the line which in turn reduces their financial payoffs as discussed in Section (2.2).[38] Since co-workers are aware of where the bottlenecks in the line are, a worker who slacks can potentially lose the benefits she derives from her network through network

[38] Unfortunately, the managements denied access to overtime and earnings data due to which we are unable to directly test the effect of network strength on earnings.

retribution. This threat of social sanctions or loss of reputation would be higher for the low performing worker, who is holding up line output. Indeed our results show that the effect of more own caste workers in the assembly line on a workers efficiency is larger for least performing worker (14–16.8 pp in col(4) of Table 4) as compared to the average worker (8.9–9.8 pp in col(4), Table 3). The lowest efficiency workers are typically younger and have been in the garment industry for fewer years, according to our data. Hence workers may want to maintain their reputation with fellow caste members so as to ensure future access to jobs and referrals.[39]

To further test for our proposed mechanism we interact a dummy for whether the job informant is still employed in the same factory or not with 'Network strength'.[40] If our mechanism is valid then we should see a significant positive coefficient on this interaction term. Our results suggest exactly that. In columns 1 -4 in Table 9, we find that almost all of the effect of network strength can be explained by its interaction with informant presence in factory. In columns 5 and 9, for line level analysis, we find a negative coefficient on informant presence on the lines minimum (column 5) or average (column 9) efficiency, but a positive coefficient on the interaction terms. The total effect of informant presence is significantly positive in columns 5 and 9, but insignificant when we account for line level unobservables, suggesting that referee presence is a line level characteristic.[41]

Knowledge spillovers through (non-network) peer effects in the workplace is more likely when co-workers can observe each other's effort or output, are performing sim-

[39] 87.1% of workers with less than 1 year of experience obtained job information from network as opposed to 49.2% of those with almost 13 years of experience.

[40] Ideally, we should interact 'Network strength' with dummy for referee in the same line as worker but we don't have information on the line of the referee.

[41] We create a dummy variable that equals 1 if work days of a worker is greater than the median number of work days (22 days) and 0 otherwise. The coefficient on the interaction of this dummy with network strength is insignificant, as shown in Table A.8. Thus those attending work for fewer days did not respond significantly differently to the network strength from those who attend more often, suggesting that social networks impact workers irrespective of the number of days they interact with each other within the factory.

ilar tasks and/or can communicate. However, as discussed previously, workers seated one behind the other in the line do not observe each other's output, and perform different operations in assembly lines. Hence spillovers are more likely to manifest in non-assembly lines. But our results, when we restrict our sample to only assembly lines in Tables 3-5, suggest that learning from peers (apart from network mediated learning) is unlikely to be driving our observed findings. We also do not find any effect on the average efficiency of peers in a line l when a high ability worker shifts from her regular line to line l on a workday. We can, thus, rule out knowledge spillovers *outside* the social network. Our theoretical model and results are, however, consistent with mentoring or knowledge spillovers which are mediated *through* the network. We find a significant coefficient on CCI interacted with proportion of workers with higher than median years of work experience in the industry in the line (Table A.9, Appendix A), suggesting that productivity of the least efficient worker increases when there are more own-caste, senior high workers in the line - indicating either monitoring or mentoring within the network.

Alternately, we might expect that conformism to an efficiency norm or altruism towards low productivity workers in the network can explain our results. The prediction then would be lower line level variance in individual output. On the contrary, we find that an increase in network strength *increases* within line variation in worker efficiency (Table A.10, Appendix A) when we estimate equation (1), rather than reducing it.[42] Hence explanations which suggest a fall in variance in efficiency within a line such as adherence to a common norm and altruism, are unlikely.[43]

[42] *All* low ability workers choose to work harder when facing an increase in own caste proportion, but higher ability workers' do not increase efficiency in response to higher own network strength in the line. We also do not find any change in variance in efficiency of workers of the same caste in a line when that group's network strength increases.

[43] Caste may be perceived as an identity rather than a network, making taste based discrimination a possible explanation of our findings. We argued in Section 3 that our caste based measure is a proxy for networks. In addition, we do not find a decline in the productivity of workers whose network strength *falls*

We conclude that economic interdependence within one's social network due to production externalities creates incentives for workers to put in greater effort. This can be facilitated when the network strength in the team is larger.

8 Conclusion

Using caste as the defining characteristic of social networks amongst workers along with exogenous variation in the caste composition of production lines across work days in garment factories in India, we show that the greater the strength of one's caste-based social network the higher the worker and line level productivity on a work day. Our findings suggest that when financial incentives are constrained , workers' social networks can be leveraged to improve efficiency.

These findings extend the literature on the role of social networks and job referrals, in general, and on productivity, in particular. They suggest that when production is team based, and tasks differ amongst the members of a team, even in the absence of explicit group based financial incentives social interdependence of group members can enforce good behavior due to the interdependence of financial payoffs emanating from production externalities at work. Although our analysis is based on garment factory production lines, the results are applicable to contexts where workers are complementary in the production process but financial compensation is fixed and at the individual level.

in a line on a workday.

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Table 1: Worker characteristics

		Caste Category		
	All	**L**	**M**	**H**
Characteristics	N=1744	N=384	N=543	N=817
Age (years)	29.637	28.130	29.516	30.426
	(0.164)	(0.336)	(0.305)	(0.234)
Female	0.850	0.813	0.823	0.885
	(0.009)	(0.020)	(0.016)	(0.011)
Hindu	0.931	0.982	0.890	0.935
	(0.006)	(0.007)	(0.013)	(0.009)
Married	0.756	0.695	0.757	0.785
	(0.010)	(0.024)	(0.018)	(0.014)
Secondary or above education	0.170	0.151	0.158	0.186
	(0.009)	(0.018)	(0.016)	(0.014)
Migrant Status				
From U.P.	0.402	0.383	0.457	0.375
	(0.012)	(0.025)	(0.021)	(0.017)
From Bihar	0.264	0.156	0.322	0.277
	(0.011)	(0.019)	(0.020)	(0.016)
Workers' Network				
Experience in garment manufacturing (years)	3.574	3.090	3.497	3.854
	(0.092)	(0.178)	(0.170)	(0.137)
Received information on this job opening	0.745	0.794	0.753	0.717
	(0.010)	(0.021)	(0.019)	(0.016)
Obtained this job through referral#	0.421	0.347	0.451	0.435
	(0.024)	(0.049)	(0.042)	(0.036)
Number of friends in this factory	1.754	1.818	1.772	1.714
	(0.034)	(0.073)	(0.062)	(0.048)
Line supervisor of same caste category##	0.349	0.052	0.655	0.287
	(0.011)	(0.011)	(0.021)	(0.016)

Note: #conditional on job informant being still employed in the factory. ##conditional on reporting correct/non-missing regular line number (N=1735). Standard errors in parentheses.

Table 2: Worker, line performance and composition

	Efficiency				Network strength
Panel A	**Worker**		**Worker-days**		
	N	Mean	N	Mean	Mean
All	1744	0.312	34,641	0.317	0.395
		(0.005)		(0.001)	(0.001)
L	384	0.308	7,604	0.309	0.248
		(0.010)		(0.003)	(0.001)
M	543	0.300	10,923	0.308	0.347
		(0.009)		(0.003)	(0.001)
H	817	0.321	16,114	0.327	0.497
		(0.007)		(0.002)	(0.001)
Panel B	**Line**		**Line-days**		
Average efficiency	37	0.298	1043	0.301	0.402
		(0.011)		(0.003)	(0.003)
Minimum efficiency	37	0.051	1043	0.050	
		(0.006)		(0.001)	

Note: Efficiency is defined as the actual output/target output. The top panel shows the average worker efficiency (overall and by caste) at worker and worker-days level. Worker efficiency is the sum of efficiency over all work days/number of work days. The network strength is measured by 'Proportion Own Caste' which is the number of workers belonging to the caste category of the worker/ total number of workers in the line on a workday. The bottom panel shows the efficiency at the line and line-day level. Average line efficiency is the mean efficiency of workers in the line; minimum line efficiency is the lowest worker efficiency in the line. Average number of workers in a line is 33. The network strength in Panel B is measured by the 'Caste Concentration Index' which is the sum of square of the shares of each caste category in a line on a day. Standard errors in parentheses.

Table 3: Worker performance and line composition

	Worker efficiency					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A (all lines)						
Network strength (β)	0.137***	0.141***	0.141***	0.140***	0.089**	0.124***
	(0.050)	(0.049)	(0.048)	(0.048)	(0.037)	(0.041)
Constant	0.110**	0.088**	0.228**	0.169**	0.011	0.080
	(0.044)	(0.039)	(0.106)	(0.083)	(0.081)	(0.086)
Number of observations	34641	34641	34641	34641	34641	34641
Number of workers	1744	1744	1744	1744	1744	1744
Number of lines	37	37	37	37	37	37
R-square	0.038	0.557	0.558	0.563	0.608	0.578
Panel B (assembly lines)						
Network strength (β)	0.195***	0.164***	0.163***	0.160***	0.098**	0.139***
	(0.046)	(0.053)	(0.052)	(0.053)	(0.041)	(0.044)
Constant	0.107*	0.062	0.213*	0.154*	-0.007	0.059
	(0.053)	(0.037)	(0.114)	(0.088)	(0.088)	(0.091)
Number of observations	32176	32176	32176	32176	32176	32176
Number of workers	1633	1633	1633	1633	1633	1633
Number of lines	31	31	31	31	31	31
R-square	0.034	0.554	0.555	0.560	0.605	0.576
Fixed effects						
Individual	No	Yes	Yes	Yes	Yes	Yes
Floor	No	No	Yes	No	No	No
Line	No	No	No	Yes	Yes	Yes
Week	No	No	No	No	Yes	No
Line x week	No	No	No	No	Yes	No
Day	No	No	No	No	No	Yes

Note: The dependent variable is the efficiency of the worker on a work day. The network strength is measured by 'Proportion Own Caste' which is the number of workers belonging to the caste category of the worker/ total number of workers in the line on a workday. Individual level controls in column 1 include dummy for H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends. All regressions control for daily line strength. Robust standard errors clustered at the line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 4: Line performance and composition

	Minimum efficiency of line				
	(1)	(2)	(3)	(4)	(5)
Panel A (all lines)					
Network strength (β)	0.064	0.105***	0.157***	0.168***	0.129***
	(0.039)	(0.028)	(0.042)	(0.036)	(0.044)
Constant	0.218**	0.256***	0.164*	0.036	0.150**
	(0.107)	(0.090)	(0.084)	(0.074)	(0.072)
Number of observations	1043	1043	1043	1043	1043
Number of lines	37	37	37	37	37
R-square	0.537	0.594	0.700	0.844	0.726
Panel B (assembly lines)					
Network strength (β)	0.046	0.114***	0.164***	0.140***	0.124***
	(0.036)	(0.033)	(0.040)	(0.035)	(0.040)
Constant	0.392***	0.309***	0.321***	0.187***	0.277***
	(0.066)	(0.082)	(0.079)	(0.065)	(0.067)
Number of observations	868	868	868	868	868
Number of lines	31	31	31	31	31
R-square	0.551	0.641	0.697	0.870	0.725
Fixed effects					
Floor	No	Yes	No	No	No
Line	No	No	Yes	Yes	Yes
Week	No	No	No	Yes	No
Line x week	No	No	No	Yes	No
Day	No	No	No	No	Yes

Note: The dependent variable is the minimum efficiency of workers in a line on a work day. The network strength is measured by the 'Caste Concentration Index' which is the sum of square of the shares of each caste category in a line on a day. Controls include average H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends on a line-day. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 5: Line performance and composition

	Average efficiency of line				
	(1)	(2)	(3)	(4)	(5)
Panel A (all lines)					
Network strength (β)	0.398***	0.320***	0.363***	0.265***	0.256***
	(0.067)	(0.069)	(0.105)	(0.091)	(0.093)
Constant	0.387**	0.359*	0.276	-0.022	0.171
	(0.190)	(0.180)	(0.256)	(0.171)	(0.238)
Number of observations	1043	1043	1043	1043	1043
Number of lines	37	37	37	37	37
R-square	0.321	0.345	0.491	0.803	0.578
Panel B (assembly lines)					
Network strength (β)	0.385***	0.421***	0.528***	0.326**	0.366***
	(0.083)	(0.075)	(0.118)	(0.128)	(0.108)
Constant	0.389	0.365	0.571	0.078	0.441
	(0.237)	(0.233)	(0.403)	(0.256)	(0.333)
Number of observations	868	868	868	868	868
Number of lines	31	31	31	31	31
R-square	0.299	0.318	0.455	0.797	0.570
Fixed effects					
Floor	No	Yes	No	No	No
Line	No	No	Yes	Yes	Yes
Week	No	No	No	Yes	No
Line x week	No	No	No	Yes	No
Day	No	No	No	No	Yes

Note: The dependent variable is the average efficiency of workers in a line on a work day. The network strength is measured by the 'Caste Concentration Index' which is the sum of square of the shares of each caste category in a line on a day. Controls include average H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends on a line-day. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 6: Worker performance and line composition (inverse probability weights)

	Worker efficiency									
	Original estimates					*With inverse probability weights*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Network strength (β)	0.141***	0.141***	0.140***	0.089**	0.124***	0.141***	0.140***	0.140***	0.089**	0.123***
	(0.049)	(0.048)	(0.048)	(0.037)	(0.041)	(0.049)	(0.049)	(0.048)	(0.037)	(0.041)
Constant	0.088**	0.228**	0.169**	0.011	0.080	0.087**	0.228**	0.169*	0.010	0.079
	(0.039)	(0.106)	(0.083)	(0.081)	(0.086)	(0.039)	(0.106)	(0.083)	(0.082)	(0.086)
Number of observations	34641	34641	34641	34641	34641	34623	34623	34623	34623	34623
R-square	0.557	0.558	0.563	0.608	0.578	0.557	0.557	0.562	0.607	0.577
Fixed Effects										
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Floor	No	Yes	No	No	No	No	Yes	No	No	No
Line	No	No	Yes	Yes	No	No	No	Yes	Yes	No
Week	No	No	No	Yes	No	No	No	No	Yes	No
Line x week	No	No	No	Yes	No	No	No	No	Yes	No
Day	No	No	No	No	Yes	No	No	No	No	Yes

Note: The dependent variable is the efficiency of the worker on a work day. The network strength is measured by 'Proportion Own Caste' which is the number of workers belonging to the caste category of the worker/ total number of workers in the line on a workday. The sample consist of all lines. Original estimates from Table 3 in columns 1-5. Regressions weighted by inverse of the probability of worker being present on a workday in columns 6-10. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 7: Worker, line performance and line composition (standard errors clustered at line-day level)

	Worker efficiency			*Line Efficiency*					
				Minimum Efficiency			*Average Efficiency*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Proportion own caste	0.140***	0.089***	0.124***						
	(0.027)	(0.024)	(0.026)						
Caste concentration index				0.157***	0.168***	0.129***	0.363***	0.265***	0.256***
				(0.034)	(0.040)	(0.034)	(0.074)	(0.094)	(0.070)
Constant	0.169**	0.011	0.080	0.164**	0.036	0.150**	0.276**	-0.022	0.171
	(0.074)	(0.079)	(0.078)	(0.066)	(0.066)	(0.066)	(0.139)	(0.133)	(0.140)
Number of observations	34641	34641	34641	1043	1043	1043	1043	1043	1043
Number of workers	1744	1744	1744	1744	1744	1744	1744	1744	1744
Number of lines	37	37	37	37	37	37	37	37	37
R-square	0.563	0.608	0.578	0.700	0.844	0.726	0.491	0.803	0.578
Fixed effects									
Individual	Yes	Yes	Yes						
Line	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week	No	Yes	No	No	Yes	No	No	Yes	No
Line x week	No	Yes	No	No	Yes	No	No	Yes	No
Day	No	No	Yes	No	No	Yes	No	No	Yes

Note:The dependent variable is the efficiency of the worker on a work day in columns 1-3; minimum efficiency in columns 4-6; average efficiency in columns 7-9. The network strength is measured by 'Proportion Own Caste', which is the number of workers belonging to the caste category of the worker/ total number of workers in the line on a workday in columns 1-3 and 'Caste Concentration Index', which is the sum of the square of the shares of each caste category in a line on a day in columns 4-9. All regressions control for daily line strength. Robust standard errors, clustered at line-day level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 8: **Job networks, residential location and caste**

Panel A: Job informant characteristic	**Number of workers**	**Proportion**
Obtained informal job information	1744	0.745
Informant was employed in this factory[@]	1300	0.648
Conditional on informant still employed in this factory:		
Informant referred worker	430	0.421
Informant was a line-worker	430	0.616
Informant employed in same line as worker[#]	203	0.192
Informant was a neighbour	430	0.521
Informant was a relative	430	0.272
Informant came from native village	430	0.051
Years informant known to worker	430	7.353
Panel B: Residential location-caste		
Same caste if residing in same town	1720	0.535
Same caste if residing in same cluster	1707	0.632
Same caste if residing in same colony	1272	0.663
Same caste if residing in same lane	848	0.832
Panel C: Residence-caste in a line	**Number of worker-days**	**Correlation**
Prop. residing in same cluster and prop. own caste in line on workday	33862	0.033***
Prop. residing in same colony and prop. own caste in line on workday	25313	0.032***
Prop. residing in same lane and prop. own caste in line on workday	16838	0.097***

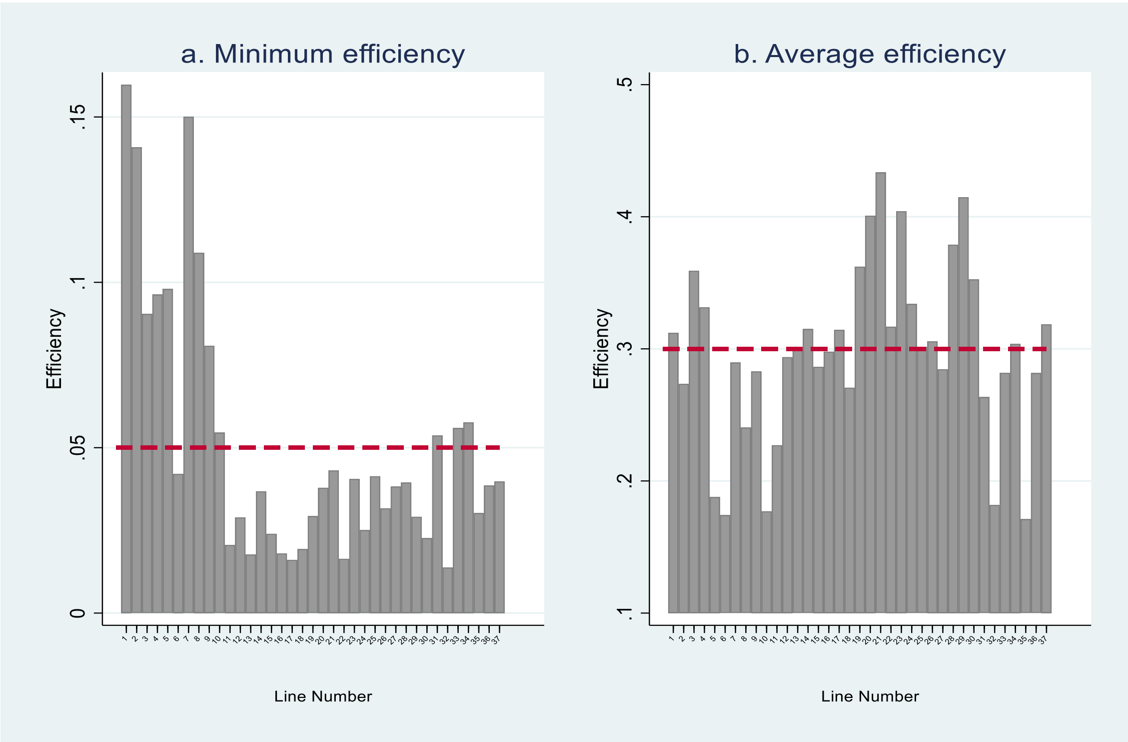
Note: [@]conditional on informal flow of job opening information; [#]smaller number of observation due non-response. In Panels B and C the sample is in worker-days, conditional on data on both caste and unit of residential location being available for a worker. Significant at *10%,**5% and ***1%.

Table 9: Worker, line performance and job referee presence

	Worker efficiency				Line Efficiency: Minimum Efficiency				Line Efficiency: Average Efficiency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Proportion own caste	0.086*	0.086*	0.038	0.066								
	(0.050)	(0.049)	(0.037)	(0.042)								
(2) Proportion own caste x referee employed in factory	0.212***	0.215***	0.207***	0.226***								
	(0.066)	(0.061)	(0.064)	(0.063)								
(3) Caste concentration index					0.015	0.112	0.116*	0.107	0.206**	0.324**	0.221	0.299**
					(0.064)	(0.066)	(0.061)	(0.065)	(0.101)	(0.157)	(0.136)	(0.138)
(4) Proportion with referee employed in factory					-0.133*	-0.053	-0.105	-0.012	-0.220	0.004	-0.027	0.163
					(0.075)	(0.064)	(0.086)	(0.075)	(0.155)	(0.206)	(0.211)	(0.216)
(5) Caste concentration index x proportion with referee employed in factory					0.370*	0.191	0.212	0.108	0.449**	0.211	0.218	-0.094
					(0.184)	(0.134)	(0.146)	(0.148)	(0.192)	(0.355)	(0.354)	(0.363)
Constant	0.229**	0.175**	0.018	0.086	0.337***	0.231***	0.114**	0.186***	0.488**	0.355	0.087	0.142
	(0.106)	(0.084)	(0.082)	(0.087)	(0.066)	(0.067)	(0.054)	(0.061)	(0.193)	(0.317)	(0.195)	(0.296)
Effect of referee employed in factory:												
(4) + (5)					0.236**	0.138	0.106	0.096	0.229**	0.216	0.191	0.069
					[0.047]	[0.124]	[0.178]	[0.288]	[0.018]	[0.269]	[0.260]	[0.702]
Number of observations	34641	34641	34641	34641	1043	1043	1043	1043	1043	1043	1043	1043
Number of workers	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744
Number of lines	37	37	37	37	37	37	37	37	37	37	37	37
R-square	0.558	0.563	0.608	0.578	0.608	0.704	0.845	0.728	0.349	0.494	0.804	0.581
Fixed effects												
Individual	Yes	Yes	Yes	Yes								
Floor	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Line	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Week	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Line x week	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Day	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

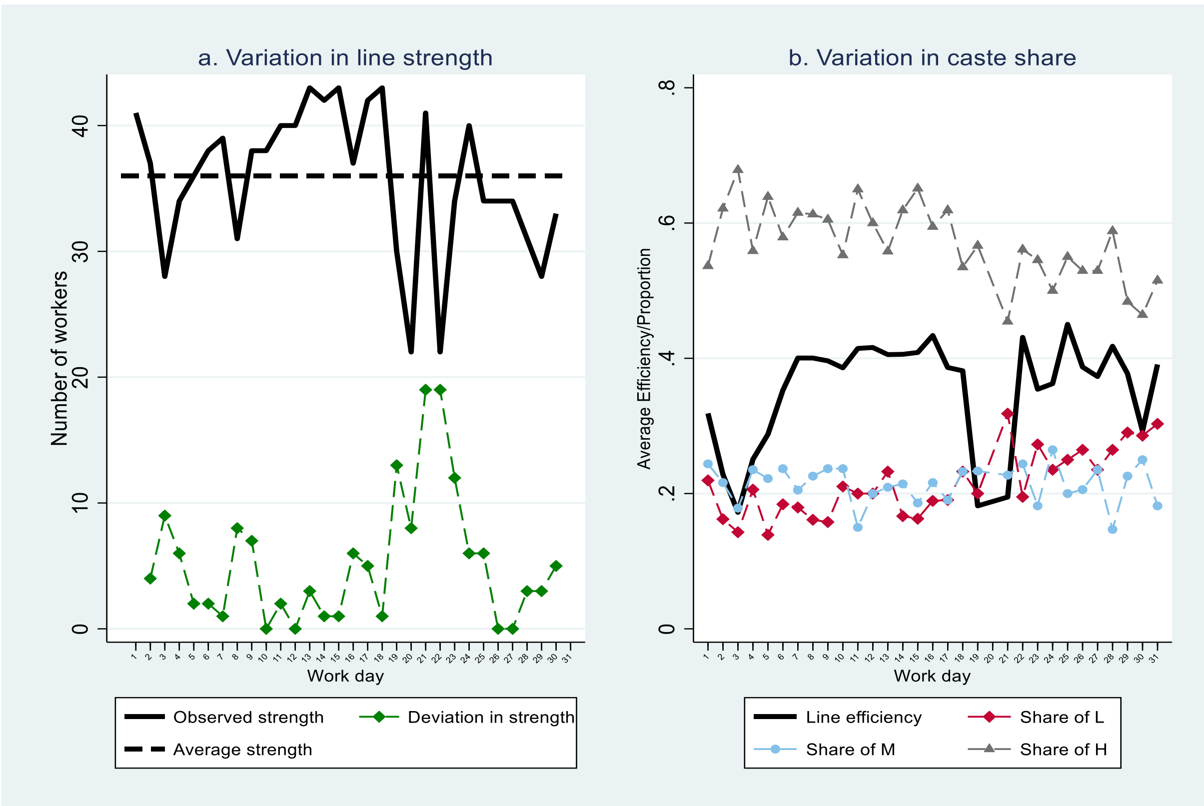
Note: In columns 1-4 the dependent variable is the efficiency of the worker on a work day. In columns 5-8 the dependent variable in the minimum efficiency of the line. In columns 9-12 the dependent variable is the average efficiency of the line. Referee employed in the factory is a dummy variable that takes value 1 if the worker's job informant (conditional on job information receipt from network) is still employed in the factory. Proportion with referee employed in factory is the proportion of workers in the line whose referee is employed in the factory (conditional on job information receipt from network). Controls include average H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends on a line-day in columns 5 and 9. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. p-values reported in square brackets. Significant at *10%, **5% and ***1%.

Figure 1: Line performance



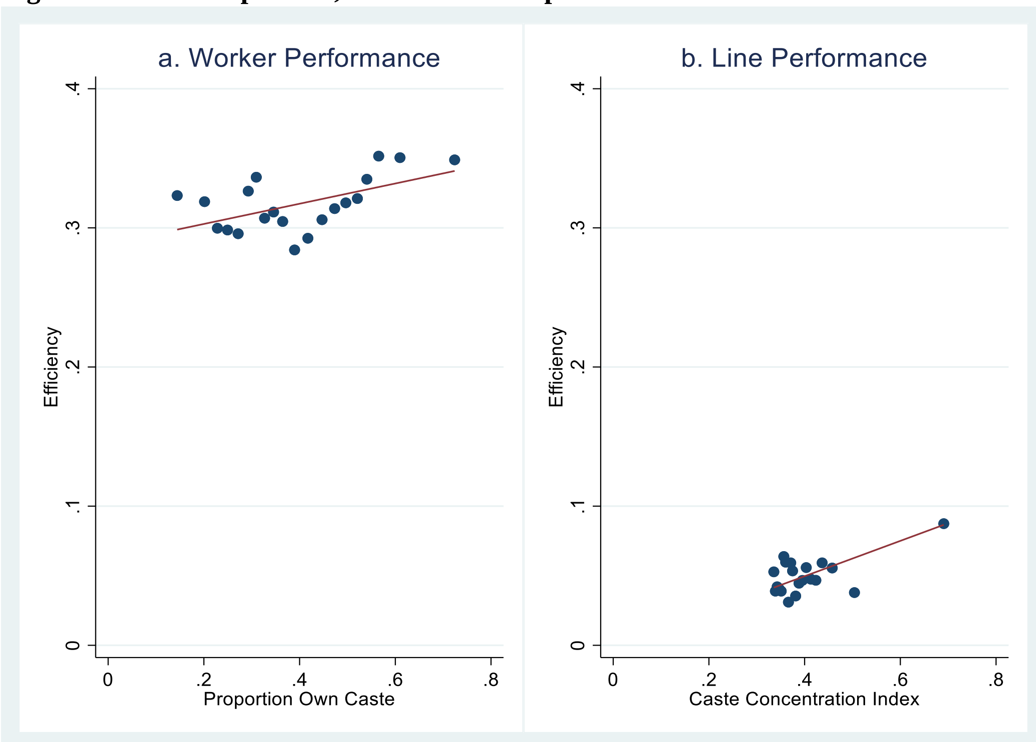
Note: Fig. 1(a) shows the mean daily minimum efficiency of each production line over workdays. Average minimum efficiency over the sample period is 0.05 (given by dashed red line). Fig. 1(b) shows the mean daily average worker efficiency of each line over workdays. Average line efficiency over the sample period is 0.30 (given by dashed red line).The number of working days for 37 production lines vary from 18 to 31 days. Production data obtained for September-October 2015 from factory records.

Figure 2: Daily variation in line composition and performance (representative line)



Note: Fig. 2(a) shows the observed line strength, average line strength (36 workers) and the absolute deviation of the line strength from the previous work day for a representative line. The allocated strength of this line is 54 workers – the number of workers who report this line to be their allotted line. Fig. 2 (b) shows the corresponding changes in each caste share and the daily average efficiency of the same line. Data obtained for September-October 2015 from factory records and worker level primary survey.

Figure 3: Caste composition, worker and line performance



Note: Fig. 1(a) shows worker level efficiency for 34,641 worker days. Worker efficiency = Daily output / Daily target output for each worker. Average efficiency per worker is 0.312. Proportion own Caste = Number of workers belonging to own caste category / Total number of workers in the line on a day; Fig. 1(b) shows the minimum worker efficiency in an assembly line on a production day for 1043 line days. Average minimum efficiency per line is 0.05. Caste concentration index=$\Sigma c^2 i$, i.e. the sum of squared share of each caste group (L, M, or H) among the workers in an assembly line on a day. Linear fit depicted in both figures using the 'binscatter' command in STATA dividing the data into 20 bins, plotting the mean X and Y values for each bin. The sample consists of 1744 workers in 37 assembly lines in two garment factories. Worker level production data obtained for September-October 2015 from factory records and caste data collected through a census survey of workers during August-October 2015.

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APPENDIX A. Additional Results

Table A.1: Worker characteristics

	Original sample	Analysis sample
Characteristics	N=1916	N=1744
Age (years)	29.44	29.64
	(0.157)	(0.164)
Female	0.848	0.850
	(0.008)	(0.009)
Hindu	0.928	0.931
	(0.006)	(0.006)
Married	0.749	0.756
	(0.010)	(0.010)
Secondary or above education	0.169	0.170
	(0.009)	(0.009)
H	0.470	0.468
	(0.012)	(0.012)
M	0.308	0.311
	(0.011)	(0.011)
L	0.222	0.220
	(0.010)	(0.010)
Migrant Status		
From U.P.	0.404	0.402
	(0.011)	(0.012)
From Bihar	0.259	0.264
	(0.010)	(0.011)
Workers' network		
Experience in garment manufacturing (years)	3.498	3.574
	(0.087)	(0.092)
Received information on this job opening	0.743	0.745
	(0.010)	(0.010)
Obtained this job through referral[#]	0.422	0.421
	(0.023)	(0.024)
Number of friends in this factory	1.735	1.754
	(0.032)	(0.034)
Line supervisor of same caste category	0.347	0.349
	(0.011)	(0.011)

Note:[#] conditional on referee being still employed in the factory. Caste data for 1857 workers in column 1. Standard errors in parentheses.

Table A.2: Chi-square test of exogeneity of caste assignment to line (export factory)

Line Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	Total
Caste Category																											
L	13	7	12	15	11	9	13	11	15	11	8	13	12	9	10	9	2	5	3	6	6	2	5	8	5	7	**227**
	10	8	10	10.2	10	10.6	9.6	8.9	10.4	11.3	13.7	9.6	12.4	10	9.8	10.9	3.5	9.8	6.7	6.5	3.7	4.8	8.7	6.3	6.7	5	**227**
	0.9	0.1	0.4	2.2	0.1	0.3	1.2	0.5	2	0	2.4	1.2	0	0.1	0	0.3	0.6	2.3	2.1	0	1.4	1.6	1.6	0.5	0.4	0.8	**23.2**
M	16	12	14	14	7	16	16	15	10	14	20	15	18	12	16	13	6	15	9	7	3	3	12	6	11	8	**308**
	13.6	10.9	13.6	13.9	13.6	14.4	13	12.1	14.1	15.3	18.6	13	16.8	13.6	13.3	14.7	4.7	13.3	9.1	8.8	5	6.5	11.8	8.5	9.1	6.8	**308**
	0.4	0.1	0	0	3.2	0.2	0.7	0.7	1.2	0.1	0.1	0.3	0.1	0.2	0.6	0.2	0.3	0.2	0	0.4	0.8	1.9	0	0.8	0.4	0.2	**13.1**
H	17	18	20	18	28	24	15	15	23	27	35	16	27	25	19	28	8	25	19	17	8	17	23	15	15	8	**510**
	22.4	18.1	22.4	22.9	22.4	23.9	21.5	20	23.4	25.4	30.7	21.5	27.8	22.4	22	24.4	7.8	22	15.1	14.6	8.3	10.7	19.5	14.2	15.1	11.2	**510**
	1.3	0	0.3	1.1	1.4	0	2	1.3	0	0.1	0.6	1.4	0	0.3	0.4	0.5	0	0.4	1	0.4	0	3.7	0.6	0.1	0	0.9	**17.6**
Total	**46**	**37**	**46**	**47**	**46**	**49**	**44**	**41**	**48**	**52**	**63**	**44**	**57**	**46**	**45**	**50**	**16**	**45**	**31**	**30**	**17**	**22**	**40**	**29**	**31**	**23**	**1045**
	46	**37**	**46**	**47**	**46**	**49**	**44**	**41**	**48**	**52**	**63**	**44**	**57**	**46**	**45**	**50**	**16**	**45**	**31**	**30**	**17**	**22**	**40**	**29**	**31**	**23**	**1045**
	2.7	**0.2**	**0.7**	**3.3**	**4.6**	**0.4**	**3.9**	**2.4**	**3.2**	**0.2**	**3.1**	**3**	**0.1**	**0.6**	**1**	**1.1**	**1**	**3**	**3.1**	**0.8**	**2.3**	**7.1**	**2.2**	**1.3**	**0.8**	**2**	**54**

Note: Data for the larger factory with 26 lines working on a randomly selected workday. There are three corresponding rows for each caste group. The first row shows the actual proportion of L/M/H in each line. The second row shows the expected proportion under the null hypothesis of independence of probability of caste and line. The third row shows the contribution of Pearsons χ^2. Pearsons χ^2 statistics is 53.975 with 50 degrees of freedom and p value =0.325. We cant reject the null hypothesis of independence of caste distribution and line composition. Similar results for all 31 workdays. p value ranges from 0.629 to 0.026 with two working days having$p$ value $<$0.05.

Table A.3: Chi-square test of exogeneity of caste assignment to line (domestic factory)

Line Number / Caste Category	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
L	4	2	1	4	4	6	4	2	4	3	**34**
	3.3	3	3.8	4.1	2.5	6.6	2.5	1	2.5	4.6	**34**
	0.1	0.4	2.1	0	0.8	0.1	0.8	1	0.8	0.5	**6.7**
M	4	5	14	9	4	12	4	1	4	9	**66**
	6.4	5.9	7.4	7.9	4.9	12.8	4.9	2	4.9	8.9	**66**
	0.9	0.1	5.9	0.2	0.2	0.1	0.2	0.5	0.2	0	**8.2**
H	5	5	0	3	2	8	2	1	2	6	**34**
	3.3	3	3.8	4.1	2.5	6.6	2.5	1	2.5	4.6	**34**
	0.9	1.3	3.8	0.3	0.1	0.3	0.1	0	0.1	0.4	7.3
Total	**0.9**	**1.3**	**3.8**	**0.3**	**0.1**	**0.3**	**0.1**	**0**	**0.1**	**0.4**	**7.3**
	13	**12**	**15**	**16**	**10**	**26**	**10**	**4**	**10**	**18**	**134**
	1.9	**1.8**	**11.8**	**0.4**	**1.1**	**0.4**	**1.1**	**1.4**	**1.1**	**1**	**22.1**

Note: Data for the smaller factory with 10 lines working on a randomly selected workday. There are three corresponding rows for each caste group. The first row shows the actual proportion of L/M/H in each line. The second row shows the expected proportion under the null hypothesis of independence of probability of caste and line. The third row shows the contribution of Pearsons χ^2. Pearsons χ^2 statistics is 22.13 with 18 degrees of freedom and p value =0.226. We cant reject the null hypothesis of independence of caste distribution and line composition. Similar results for all 31 workdays. p value ranges from 0.802 to 0.017 with three working days having p value<0.05.

Table A.4: Worker attendance, production targets and caste composition

	Worker level		*Line level (SAM)*	
	Present rate	**Work-days**	**Target**	**Lag-target**
	(1)	(2)	(3)	(4)
Age (years)	0.001***	0.058	1.350	1.050
	(0.000)	(0.035)	(0.885)	(0.827)
Married	-0.013*	-1.566***	1.855	15.012
	(0.007)	(0.515)	(10.119)	(9.178)
Female	-0.006	1.788***	-27.293**	-24.738**
	(0.008)	(0.562)	(11.968)	(11.495)
Native state Bihar	0.010**	0.465	-9.064	-6.586
	(0.005)	(0.295)	(10.345)	(7.879)
Hindu	0.033***	2.076***	9.164	2.066
	(0.010)	(0.617)	(12.376)	(11.272)
Secondary education or more	0.003	0.172	9.926	9.577
	(0.005)	(0.410)	(12.498)	(12.929)
Obtained job information informally	0.000	0.874*	-10.704	-8.598
	(0.006)	(0.464)	(8.105)	(7.689)
Experience (years)	-0.001***	0.233***	-2.140**	-1.942**
	(0.000)	(0.056)	(0.951)	(0.899)
Number of reported friends	0.000	0.205	-1.336	-2.379
	(0.002)	(0.124)	(1.962)	(2.287)
Line strength	-0.000***	-0.204***	0.128*	0.143**
	(0.000)	(0.009)	(0.068)	(0.061)
H	0.003	-0.371		
	(0.006)	(0.285)		
M	0.006	0.177		
	(0.007)	(0.438)		
Line supervisor same caste	0.003	0.197		
	(0.005)	(0.275)		
Caste concentration index			4.500	1.073
			(10.581)	(11.056)
Constant	0.882***	16.231***	6.878	8.264
	(0.013)	(0.768)	(32.140)	(31.634)
Number of observations	1731	1731	751	681
Number of workers	1731	1731	1548	1548
Number of lines	37	37	27	27
R-square	0.052	0.197	0.462	0.485
Line Fixed Effects	Yes	Yes	Yes	Yes

Note: Col (1) uses factory attendance data. 'Attendance rate' is the number of days present/number of on-roll days for each worker (excluding half days, forming 0.45 of the attendance person days). The mean attendance rate is 0.923. Col (2) is based on the production data. 'Work-days' is the count of days a worker appears in the productivity data (excluding half days, 0.30% of the worker days). Attendance data missing for 4 workers; reported line information missing for 9 workers. Individual level controls as elucidated in Table 3. Sample in cols (3)-(4) conditional on availability of line-daily target (SAM for 1 finished product). Dependent variable in col (3) (col(4)) is line-daily target on day t (t-1). Some lines did not operate the day before, hence missing observations in col (4). Line-day level controls as elucidated in Table 4. Robust standard errors, clustered at the line level, in parentheses. Significant at *10%, **5% and ***1%.

Table A.5: Worker performance and composition (with style fixed effects)

	Worker level				
	(1)	(2)	(3)	(4)	(5)
Proportion own caste	0.146***	0.137***	0.108**	0.109**	0.111**
	(0.050)	(0.049)	(0.044)	(0.044)	(0.043)
Constant	0.099*	-0.307***	-0.281***	-0.283***	-0.280***
	(0.058)	(0.079)	(0.075)	(0.078)	(0.080)
Number of observations	30621	30621	30621	30621	30621
Number of workers	1548	1548	1548	1548	1548
Number of lines	27	27	27	27	27
Number of styles	45	45	45	45	45
R-square	0.581	0.584	0.591	0.595	0.597
Fixed effects					
Individual	Yes	Yes	Yes	Yes	Yes
Style	Yes	Yes	Yes	Yes	Yes
Line	No	Yes	Yes	Yes	Yes
Line x style	No	No	Yes	Yes	Yes
Week	No	No	No	Yes	No
Day	No	No	No	No	Yes

Note: The sample consists of assembly lines (exporting factory) for which we have daily-style information. On average, 2.8 unique styles ran per line during our sample period. The dependent variable is the efficiency of the worker on a work day. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table A.6: Line performance and composition (with style fixed effects)

	Minimum efficiency				*Average efficiency*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Caste concentration index	0.203***	0.163***	0.158***	0.158***	0.526***	0.428***	0.377***	0.404***
	(0.046)	(0.044)	(0.044)	(0.043)	(0.127)	(0.116)	(0.120)	(0.118)
Constant	0.106	0.113*	0.092	0.101*	0.253	0.387	0.209	0.378*
	(0.065)	(0.062)	(0.060)	(0.057)	(0.219)	(0.228)	(0.212)	(0.204)
Number of observations	765	765	765	765	765	765	765	765
Number of lines	27	27	27	27	27	27	27	27
Number of styles	45	45	45	45	45	45	45	45
R-square	0.603	0.648	0.657	0.663	0.693	0.725	0.751	0.764
Fixed effects								
Style	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line x style	No	No	Yes	Yes	No	No	Yes	Yes
Week	No	No	Yes	No	No	No	Yes	No
Day	No	No	No	Yes	No	No	No	Yes

Note: The sample consists of assembly lines (exporting factory) for which we have daily-style information. On average, 2.8 unique styles ran per line during our sample period. The dependent variable is minimum efficiency in columns 1-4; average efficiency in columns 5-8. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table A.7: Worker, line performance and composition (bootstrap standard errors)

	Worker efficiency				*Line Efficiency*							
					Minimum Efficiency				*Average Efficiency*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Proportion own caste	0.141***	0.140***	0.089**	0.124***								
	[0.006]	[0.001]	[0.014]	[0.002]								
Caste concentration index					0.157***	0.157**	0.168***	0.129**	0.363***	0.363***	0.265***	0.256***
					[0.004]	[0.011]	[0.000]	[0.036]	[0.006]	[0.004]	[0.010]	[0.006]
Constant	0.088**	0.169	0.011	0.080	0.066	0.164	0.036	0.150*	0.248	0.276	-0.022	0.171
	[0.016]	[0.193]	[0.937]	[0.555]	[0.571]	[0.122]	[0.664]	[0.088]	[0.411]	[0.302]	[0.925]	[0.492]
Number of observations	34641	34641	34641	34641	1043	1043	1043	1043	1043	1043	1043	1043
Number of workers	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744	1744
Number of lines	37	37	37	37	37	37	37	37	37	37	37	37
R-square	0.557	0.030	0.129	0.063	0.246	0.700	0.844	0.726	0.123	0.491	0.803	0.578
Fixed effects												
Individual	Yes	Yes	Yes	Yes								
Line	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Line x week	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Day	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Note: The sample consist of all lines. p-values in parentheses. The network strength is measured by 'Proportion Own Caste' which is the number of workers belonging to the caste category of the worker/ total number of workers in the line on a workday in columns 1-4, and by the 'Caste Concentration Index' which is the sum of square of the shares of each caste category in a line on a day in columns 5-12. Regressions results with pairwise bootstrapped standard errors clustered at line level in column 1; pairwise bootstrapped standard errors in columns 2-4, 5, 9. One of the limitation of available bootstrap procedures is that they do not run if the units of observation shifts across clusters with fixed effects at the clustering unit. Since individuals move across lines in our data, we are not able to run worker level specifications with line fixed effects and bootstrapped standard errors clustered at line level. The line-level data does not pose such challenge and we present wild cluster bootstrapped standard errors (at line level) in col (6)-(8) and (10)-(12). All regressions control for daily line strength. 2000 replications across all regressions. Significant at *10%, **5% and ***1%.

Table A.8: Worker performance and work days

	Worker level					
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion own caste	0.158***	0.078	0.077	0.080	0.018	0.065
	(0.057)	(0.062)	(0.060)	(0.057)	(0.057)	(0.055)
Proportion own caste x	-0.034	0.099	0.100	0.094	0.113	0.092
Above median attendance	(0.064)	(0.070)	(0.069)	(0.070)	(0.071)	(0.068)
Constant	0.095*	0.086**	0.226**	0.173**	0.017	0.084
	(0.049)	(0.039)	(0.105)	(0.082)	(0.081)	(0.085)
Number of observations	34641	34641	34641	34641	34641	34641
Number of workers	1744	1744	1744	1744	1744	1744
Number of lines	37	37	37	37	37	37
R-square	0.039	0.557	0.558	0.563	0.608	0.578
Fixed effects						
Individual	No	Yes	Yes	Yes	Yes	Yes
Floor	No	No	Yes	No	No	No
Line	No	No	No	Yes	Yes	Yes
Week	No	No	No	No	Yes	No
Line x week	No	No	No	No	Yes	No
Day	No	No	No	No	No	Yes

Note: The dependent variable is the efficiency of the worker on a work day. Individual level controls in column 1 include dummy for H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends. Above median attendance is a dummy variable that takes value 1 if the number of work days of a worker $\geq$ median work days; 0 otherwise. Median working days = 22. Individual controls in column 1 include dummy for H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience, and number of reported co-workers who are friends. All regressions control for daily line strength. Robust standard errors, clustered at the line level, in parentheses. Significant at *10%,**5% and ***1%.

Table A.9: Worker performance, experience and network strength

	Minimum efficiency				
	(1)	(2)	(3)	(4)	(5)
Caste concentration index	-0.158*	-0.113	-0.028	-0.026	-0.095
	(0.086)	(0.084)	(0.087)	(0.123)	(0.081)
Proportion high experience	-0.262***	-0.238***	-0.170***	-0.159***	-0.181***
	(0.077)	(0.073)	(0.054)	(0.058)	(0.048)
Proportion high experience x CCI	0.512***	0.501***	0.399**	0.360	0.479***
	(0.171)	(0.164)	(0.149)	(0.216)	(0.145)
Constant	0.342***	0.341***	0.265***	0.118	0.266***
	(0.078)	(0.063)	(0.079)	(0.078)	(0.071)
Number of observations	1043	1043	1043	1043	1043
Number of lines	37	37	37	37	37
R-square	0.570	0.618	0.709	0.848	0.737
Fixed effects					
Floor	No	Yes	No	No	No
Line	No	No	Yes	Yes	Yes
Week	No	No	No	Yes	No
Line x week	No	No	No	Yes	No
Day	No	No	No	No	Yes

Note: The dependent variable is the minimum efficiency of workers in a line on a work day. 'Proportion high experience' is the number of workers with above or equal to median years of experience in the garment industry sitting in line l on day d /strength in line l on day d. Median experience in garment industry for 1744 workers is 2.129 years. Controls include average H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends on a line-day. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table A.10: Dispersion in worker performance and network strength

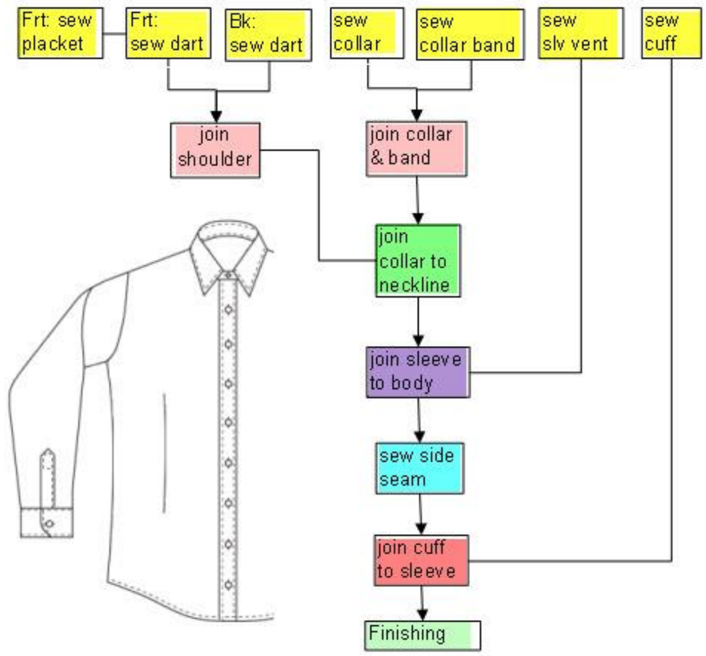
	Dispersion in worker productivity				
	(1)	(2)	(3)	(4)	(5)
Network strength (β)	0.204***	0.123***	0.150**	0.090	0.142**
	(0.051)	(0.040)	(0.070)	(0.057)	(0.070)
Constant	0.162	0.142	0.021	0.008	-0.025
	(0.125)	(0.106)	(0.153)	(0.109)	(0.161)
Number of observations	1041	1041	1041	1041	1041
Number of lines	37	37	37	37	37
R-square	0.465	0.543	0.619	0.823	0.631
Fixed effects					
Floor	No	Yes	No	No	No
Line	No	No	Yes	Yes	Yes
Week	No	No	No	Yes	No
Line x week	No	No	No	Yes	No
Day	No	No	No	No	Yes

Note: The dependent variable is the standard deviation of efficiency of all workers sitting in line l on day d. We lose 2 line-days with line strength of 1 worker out of 1043 line-days while calculating standard deviation. Controls include average H, M, age, married, woman, Hindu, migrant from Bihar, received information on job opening through network, secondary or higher level of education, years of experience and number of reported co-workers who are friends on a line-day. All regressions control for daily line strength. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Figure A1: Factory floor and line organisation

Location: Faridabad
Source: icrw.org

Figure A2: Manufacturing process of a shirt



Source:https://www.pinterest.co.uk/neelamparveen78/garment-production-manufacturing

APPENDIX B: Theoretical Framework

In a setting where worker effort is imperfectly observed, or, equivalently, is non-verifiable, firms face the usual moral hazard problem. In an assembly line if some workers are expected to put in low levels of effort then the whole line may be stuck in a bad equilibrium with low output. Since there are complementarities in production, team incentives seem intuitively the right solution though there are still free riding issues (see e.g. Itoh (1991), Che and Yoo (2001) for team incentives using peer sanctioning to encourage cooperation when there is moral hazard). In the factory we did not observe any explicit team pay. However we did observe a lot of individual incentives such as overtime pay. Moreover promotions between different grades also act as individual incentives. Although incentives are individual, note that the supervisor is the one who decides on overtime and also to some extent on promotions. Since the supervisor cares about team output, the incentives are implicitly team incentives. Indeed, as long as the production function has complementarities, it is impossible for an individual worker to increase his own productivity if others do not cooperate. We therefore model (implicit) wage contracts based on joint output. We assume workers are risk neutral, and there is a minimum wage of $\underline{w}$ in the industry.

Formally, suppose there are two workers in the firm (the model is easily generalized to more workers) characterized by their observable ability types $\theta_i \in \{\bar{\theta}, \underline{\theta}\}$.[44] Output of worker i is increasing in θ and effort. For simplicity we assume the production function for worker i is given by $y_i = \theta_i + X$, where X is a random variable that takes one of the values $\{x_1, x_2\}$ with $x_1 > x_2$. The production function therefore has an individual component θ_i and a joint component, X which depends on the profile of efforts by the two workers. Average line output is the minimum of the y_i.

[44] Usually workers in an assembly line are of different grades, based on their efficiency levels.

A line can have workers of different productivity: in our model we can have either both high ability, both low ability or one low and one high ability worker. Line output is highest when workers are high ability and put in high effort.

Workers choose from two levels of effort $e_i \in \{h, l\}$ with $h > l$. The cost of effort is given by $c(e) = c$, if $e = h$ and $c(e) = 0$ if $e = l$. Below we focus only on the joint components part of the production function, since θ_i is fixed and does not change with incentives. We also assume first that $\theta_i \neq \theta_j$.

The probability of obtaining output level x_1 is denoted by α^{e_i,e_j}. If both workers choose $e_i = h$ the expected output is $\pi_{h,h} = \alpha^{hh}x_1+(1-\alpha^{hh})x_2$. When effort levels are not equal then it is likely that expected output in this case depends on whether the high ability or the low ability worker is putting in high effort. This captures situations where the supervisor might ask a high ability worker to help a low productivity worker. Thus we assume that when $i \neq j$ then π_{e_i,e_j} depends also on the ability levels of workers i, j. In particular $\bar{\pi}_{h,l} = (\pi_{h,l}|\theta_i = \bar{\theta}, \theta_j = \underline{\theta}) > \underline{\pi}_{h,l} = (\pi_{h,l}|\theta_i = \underline{\theta}, \theta_j = \bar{\theta})$. Denote $\bar{\alpha}^{hl}$ ($\underline{\alpha}^{hl}$) as the probability of high output when the high (low) ability worker puts in high effort and the low (high) ability worker puts in low effort. Therefore, $\bar{\pi}_{h,l} = \bar{\alpha}^{hl}x_1 + (1 - \bar{\alpha}^{hl})x_2$ and $\underline{\pi}_{h,l} = \underline{\alpha}^{hl}x_1 + (1 - \underline{\alpha}^{hl})x_2$. Finally, if both workers choose low effort then expected output is $\pi_{l,l} = \alpha^{ll}x_1+(1-\alpha^{ll})x_2$. Higher effort always increases output so $\pi_{h,h} > \bar{\pi}_{h,l} > \underline{\pi}_{h,l} > \pi_{l,l}$ which implies $\alpha^{hh} > \bar{\alpha}^{hl} > \underline{\alpha}^{hl} > \alpha^{ll}$ and complementarity in effort levels implies that $\pi_{h,h} - \bar{\pi}_{h,l} > \bar{\pi}_{h,l} - \pi_{l,l}$, and $\pi_{h,h} - \underline{\pi}_{h,l} > \underline{\pi}_{h,l} - \pi_{l,l}$. This implies $\alpha^{hh} - \bar{\alpha}^{h,l} > \bar{\alpha}^{h,l} - \alpha^{ll}$, and $\alpha^{hh} - \underline{\alpha}^{h,l} > \underline{\alpha}^{h,l} - \alpha^{ll}$.

First we show that if minimum worker's ability on the line ($\underline{\theta}$) is very low, then it may not be possible to induce high effort from the low ability worker in the absence of social networks. This is because, in order to induce the lowest ability workers to put in high effort, the wages have to be higher than the worker's contribution to output. Put another way the expected overtime and promotions needed to incentivize the worker is too costly relative to the gain in line output. Therefore the solution might be either that only high ability workers put in high effort or none of the types do.

B.1 Benchmark case without social networks

In this section we show the conditions under which the firm can induce high effort by workers when social networks are not present.

Let worker's utility function be:

$$u_i(e_i, e_j) = E(w|e_i, e_j) - c(e_i) \tag{B.1.1}$$

where $E(w|e_i, e_j)$ is the expected wage given the effort profile e_i, e_j. We can compute expected profits under three cases: (1) when the firm induces high effort from both workers, (2) when the firm induces high effort from only one worker and (3) when the firm does not induce high effort from any worker.

Case 1: The *per worker* expected profit of the firm (for a worker with ability θ), if it wants to induce high effort from both workers is, therefore, given by: $E(\pi|e_h, e_h) = \theta + \pi_{h,h} - (\alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2)$ The optimization problem is to choose w_1, w_2 to maximize (per worker expected profit)

$$\theta + E(\pi(e_h, e_h)) = \theta + \pi_{h,h} - \alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2 \tag{B.1.2}$$

subject to the participation constraints (PC), the incentive compatibility (IC) constraints and a limited liability (LL) constraint. Notice that θ appears on both sides of the inequality and therefore drops out in the conditions. Let $\bar{w}_1$ and $\bar{w}_2$ denote the wages for a high ability worker and $\underline{w}_1$ and $\underline{w}_2$ denote the wages for a low ability worker

(1) The PC is that a worker will only accept the implicit contract offering expected

wages $E(w|h,h)$ if the cost of effort is low enough so that utility is higher than the outside option of minimum wages in another firm:

$$\alpha^{hh}\bar{w}_1 + (1-\alpha^{hh})\bar{w}_2 - c \geq \underline{w} \tag{B.1.3}$$

and

$$\alpha^{hh}\underline{w}_1 + (1-\alpha^{hh})\underline{w}_2 - c \geq \underline{w} \tag{B.1.4}$$

(2) The ICs are that, given complementarity, the firm must take account of the other worker's effort in designing the incentive wages. Below we have conditions IC(1) and IC(2) that ensure (a) that high effort is a dominant strategy for a high ability worker i: IC(1) (given worker j puts in high effort):

$$\alpha^{hh}\bar{w}_1 + (1-\alpha^{hh})\bar{w}_2 - c \geq \bar{\alpha}^{lh}\bar{w}_1 + (1-\bar{\alpha}^{lh})\bar{w}_2 \tag{B.1.5}$$

and IC(2) (given worker j puts in low effort):

$$\bar{\alpha}^{hl}\bar{w}_1 + (1-\bar{\alpha}^{hl})\bar{w}_2 - c \geq \alpha^{ll}\bar{w}_1 + (1-\alpha^{ll})\bar{w}_2 \tag{B.1.6}$$

(b) Conditions IC'(1) and IC'(2) that ensure (a) that high effort is a dominant strategy for a low ability worker i: IC'(1) (given worker j puts in high effort):

$$\alpha^{hh}\underline{w}_1 + (1-\alpha^{hh})\underline{w}_2 - c \geq \underline{\alpha}^{lh}\underline{w}_1 + (1-\underline{\alpha}^{lh})\underline{w}_2 \tag{B.1.7}$$

and IC'(2) (given worker j puts in low effort):

$$\underline{\alpha}^{hl}\underline{w}_1 + (1-\underline{\alpha}^{hl})\underline{w}_2 - c \geq \alpha^{ll}\underline{w}_1 + (1-\alpha^{ll})\underline{w}_2 \tag{B.1.8}$$

and (3) the LL constraint: $\bar{w}_1, \bar{w}_2, \underline{w}_1, \underline{w}_2 \geq \underline{w}$.

Lemma 1 *The solution to the maximization problem (B.1.2) for the high ability worker is* $\bar{w}_1 = \underline{w} + \frac{c}{\bar{\alpha}^{hl} - \alpha^{ll}}$ *and* $\bar{w}_2 = \underline{w}$ *and for the low ability worker is* $\underline{w}_1 = \underline{w} + \frac{c}{\underline{\alpha}^{hl} - \alpha^{ll}}$ *and* $\underline{w}_2 = \underline{w}$

Proof

We show the result for the high ability worker: The IC constraints for the high ability worker can be re-written as:

$$(\alpha^{hh} - \bar{\alpha}^{lh})(\bar{w}_1 - \bar{w}_2) \geq c \tag{B.1.9}$$

and

$$(\bar{\alpha}^{hl} - \alpha^{ll})(\bar{w}_1 - \bar{w}_2) \geq c \tag{B.1.10}$$

Since $(\alpha^{hh} - \bar{\alpha}^{hl}) > (\bar{\alpha}^{lh} - \alpha^{ll})$, IC (B.1.10) $\implies$ IC(B.1.9). Moreover IC (B.1.10) $\implies$ $\bar{w}_1 > \bar{w}_2$. Let $\bar{w}_2 = w$ be the base wage and $\bar{w}_1 - \bar{w}_2 = b$, the bonus. Then we have the following solution $\bar{w}_1 = w + b = \underline{w} + \frac{c}{\bar{\alpha}^{hl} - \alpha^{ll}}$ and $\bar{w}_2 = \underline{w}$. This solution satisfies the PC.

The same logic implies the solution for $\underline{w}_1$ and $\underline{w}_2$. ■

Expected profits for the high ability worker are $= \bar{\theta} + \pi_{h,h} - \alpha^{hh}(\frac{c}{\bar{\alpha}^{hl} - \alpha^{ll}}) - \underline{w}$, and for the low ability worker are $= \underline{\theta} + \pi_{h,h} - \alpha^{hh}(\frac{c}{\underline{\alpha}^{hl} - \alpha^{ll}}) - \underline{w}$. It is easy to see that profits are lower for the low ability worker both because θ is lower but also because the compensation needed to induce high effort is higher. Thus if e.g. $\underline{\theta} + \pi_{h,h} < \alpha^{hh}(\frac{c}{\underline{\alpha}^{hl} - \alpha^{ll}}) + \underline{w}$, then a scheme to induce high effort in both workers is not profitable for the firm. It can however cap wages at the expected productivity of the low ability worker $\underline{\theta} + \pi_{h,h}$. At this wage rate the low ability worker strictly prefers to put in low effort. Therefore the contractual wages shift to a different regime as Lemma 2 below shows.

Lemma 2 *If the firm induces high effort from the high ability worker and low effort from the low ability worker then wages of the high ability worker are given by:* $\tilde{w}_2 = \underline{w}, \tilde{w}_1 = \underline{w} + \frac{c}{(\bar{\alpha}^{hl} - \alpha^{ll})}$. *The low ability worker gets* $\underline{w}$.

Proof:

The problem for the high ability worker is to choose w_1, w_2 to maximize:

$$E(\pi(e_h, e_l)) = \bar{\theta} + \bar{\pi}_{h,l} - \bar{\alpha}^{hl}\tilde{w}_1 + (1 - \bar{\alpha}^{hl})\tilde{w}_2 \tag{B.1.11}$$

subject to:

(1) the PC:

$$\bar{\alpha}^{hl}\tilde{w}_1 + (1 - \bar{\alpha}^{hl})\tilde{w}_2 - c \geq \underline{w} \tag{B.1.12}$$

which can be re-written as:

$$\bar{\alpha}^{hl}(\tilde{w}_1\tilde{w}_2) + \tilde{w}_2 - c \geq \underline{w} \tag{B.1.13}$$

(2) The IC which can be re-written as:

$$(\bar{\alpha}^{hl} - \alpha^{ll})(\tilde{w}_1 - \tilde{w}_2) \geq c \tag{B.1.14}$$

and (3) the LL constraint: $\tilde{w}_1, \tilde{w}_2 \geq \underline{w}$

The proof follows the same logic as the proof of Lemma (1). By the same logic, $\tilde{w}_2 = \underline{w}, \tilde{w}_1 = \underline{w} + \frac{c}{(\bar{\alpha}^{hl} - \alpha^{ll})}$. ■

Expected profits are positive iff $\bar{\theta} + \bar{\pi}_{h,l} - \bar{\alpha}^{hl}(\frac{c}{\bar{\alpha}^{hl} - \alpha^{ll}}) - \underline{w} \geq 0$.

A third option for the firm is to simply not induce high effort in both workers and pay minimum wages to both workers. In this case profits are positive iff $\underline{\theta} + \pi_{ll} - \underline{w} \geq 0$.

Proposition 1 *Suppose $\theta_i \neq \theta_j$. Assume that the minimum ability in the line satisfies $\underline{\theta} \geq T_1 \equiv \alpha^{hh}(\frac{c}{\underline{\alpha}^{hl}-\alpha^{ll}}) + \underline{w} - \pi_{h,h}$, then both workers put in high effort and (average) line output is $\underline{\theta} + \pi_{h,h}$. If $\alpha^{hh}(\frac{c}{\bar{\alpha}^{hl}-\alpha^{ll}}) + \underline{w} - \pi_{h,h} \equiv T_2 \leq \underline{\theta} < T_1$ then only the high ability worker puts in high effort, line output is $\underline{\theta} + \bar{\pi}_{h,l}$. Finally, if $\underline{\theta} < T_2$, then both workers put in low effort and line output is $\underline{\theta} + \pi_{l,l}$.*

Proposition 2 *Assume $\theta_i = \theta_j = \bar{\theta}$, then both high ability workers put in high effort iff $\bar{\theta} \geq T_2$. Assume $\theta_i = \theta_j = \underline{\theta}$, then both low ability workers put in high effort iff $\underline{\theta} \geq T_1$*

The proof is obvious and follows from lemmas above.

Suppose that $\underline{\theta} \geq T_1$, while $\bar{\theta} \geq T_2$ then in any symmetric equilibrium, the line output is $\bar{\theta} + \pi_{h,h}$ when $\theta_i = \theta_j = \bar{\theta}$ and is $\underline{\theta} + \pi_{l,l}$ when $\theta_i = \theta_j = \underline{\theta}$.

B.2 With social networks

There is an exogenous probability of separation from the firm $1 - \gamma(\theta)$, which is higher for low ability workers, $\gamma(\underline{\theta}) < \gamma(\bar{\theta})$, as chances of being fired are higher even for the same effort levels. W.l.o.g we assume that $\gamma(\bar{\theta})$ is normalised to 1, so that $\gamma(\underline{\theta}) = \gamma \in (0, 1)$. Separated workers rely on their social networks, in particular on more experienced workers for getting other jobs via referrals or for helping over a financially difficult period. We denote the utility from the network as $V(f_i^k|e_i)$ where f_i^k is the number (or fraction) of coworkers in the social network of worker i of caste k in the line. When monitoring/mentoring is feasible then V can be conditioned on effort of worker i (in our setting, low output workers who are holding up line output are often called out by the supervisor- this observability is all that is needed for the model). The higher the number of co-workers from one's social network, the higher is V, because co-workers of the same network are likely to observe worker i if called out for holding up the line by supervisor, live close to worker i and have links with other network members who can help/ostracize the worker, and may themselves not provide referrals to the worker in future. The larger the strength of the network on the line or in the factory, the better is information transmission on worker i to others in the network but outside the line/factory. We assume that the share of other out group or out of network peers in the line does not affect workers.

The key point in the formal model is to introduce an extra term in the incentive and participation constraints for low ability workers that depends on γ and $V(\cdot)$. For ease of exposition we focus on the low ability worker only, as that is the binding constraint on line output. Let wages for the low ability worker be denoted as $\hat{w}_1, \hat{w}_2$.

The utility function for worker i in network k is:

$$u_i(e_i, e_i)_i^k = \gamma(E(w|e_h, e_h) - c(e_i)) + (1-\gamma)V(f_i^k|e_i) \tag{B.2.1}$$

Assume that monitoring or mentoring by high ability workers is profitable, i.e. $\alpha^{hh}\bar{w}_1 - \underline{m} > \bar{\alpha}^{hl}\tilde{w}_1$, high ability workers benefit from monitoring/ helping/mentoring low ability workers as they get a higher expected wage when line output is higher. In this case, $V(f_i^k|e)$ depends on the effort level of worker i and $V(f_i^k|e_l) = \underline{V} < V(f_i^k|e_h)$. We can re-write the constraints for low ability worker as follows: (1) the PC:

$$\alpha^{hh}\hat{w}_1 + (1-\alpha^{hh})\hat{w}_2 \geq c + \underline{w} - \frac{(1-\gamma)}{\gamma}(V(f_i^k|e_h) - \underline{V}) \tag{B.2.2}$$

(2) The ICs

$$\gamma(\alpha^{hh}\hat{w}_1 + (1-\alpha^{hh})\hat{w}_2 - c) + (1-\gamma)V(f_i^k|e_h) \geq \gamma(\underline{\alpha}^{lh}\hat{w}_1 + (1-\underline{\alpha}^{lh})\hat{w}_2) + (1-\gamma)\underline{V} \tag{B.2.3}$$

which can be re-written as:

$$(\alpha^{hh} - \underline{\alpha}^{lh})(\hat{w}_1 - \hat{w}_2) \geq c - \frac{1-\gamma}{\gamma}(V(f_i^k|e_h) - \underline{V}) \tag{B.2.4}$$

and

$$\gamma(\underline{\alpha}^{hl}\hat{w}_1 + (1-\underline{\alpha}^{hl})\hat{w}_2 - c) + (1-\gamma)V(f_i^k|e_h) \geq \gamma(\alpha^{ll}\hat{w}_1 + (1-\alpha^{ll})\hat{w}_2) + (1-\gamma)\underline{V} \tag{B.2.5}$$

which can be re-written as:

$$(\underline{\alpha}^{hl} - \alpha^{ll})(\hat{w}_1 - \hat{w}_2) \geq c - \frac{1-\gamma}{\gamma}(V(f_i^k|e_h) - \underline{V}) \tag{B.2.6}$$

and (3) the LL constraint: $\hat{w}_1, \hat{w}_2 \geq \underline{w}$

Denote $\frac{1-\gamma}{\gamma}(V(f_i^k|e_h) - \underline{V}) = K$. Using the same proof as in Lemma 1 and 2, the wages to induce high effort from worker 2 satisfy: $\hat{w}_2 = \underline{w}, \hat{w}_1 \geq \underline{w} + \frac{c-K}{(\underline{\alpha}^{hl}-\alpha^{ll})}$. The high ability worker gets as above, $\bar{w}_1, \bar{w}_2$.

The implication of monitoring or mentoring of low ability workers and being able to condition network benefits on effort is that low ability workers will have a higher chance of putting in high effort even with a lower monetary payoff from the firm. High ability workers gain from monitoring/mentoring when the costs of doing so are low compared to the higher probability of getting overtime or being promoted. Low ability workers also get a higher monetary payoff if the firm finds it profitable i.e. $\underline{\theta} \geq \alpha^{hh}\hat{w}_1 + \underline{w} - \pi_{h,h}$.

Let $\alpha^{hh}(\frac{K}{\underline{\alpha}^{hl}-\alpha^{ll}}) \equiv k_1$ and $\alpha^{hh}(\frac{K}{\bar{\alpha}^{hl}-\alpha^{ll}}) \equiv k_2$. Then $\alpha^{hh}(\frac{c-K}{\underline{\alpha}^{hl}-\alpha^{ll}}) + \underline{w} - \pi_{h,h} = T_1 - \alpha^{hh}(\frac{K}{\underline{\alpha}^{hl}-\alpha^{ll}}) = T_1 - k_1$ and $\alpha^{hh}(\frac{c-K}{\bar{\alpha}^{hl}-\alpha^{ll}}) + \underline{w} - \pi_{h,h} = T_2 - \alpha^{hh}(\frac{K}{\bar{\alpha}^{hl}-\alpha^{ll}}) = T_2 - k_2$.

Proposition 3 *Assume that $\theta_i \neq \theta_j$ and the minimum ability in the line satisfies*

$\underline{\theta} \geq T_1 - k_1$, then both workers put in high effort and line output is $\underline{\theta} + \pi_{h,h}$. If $T_2 - k_2 \leq \underline{\theta} < T_1 - k_1$, then only the high ability worker puts in high effort and line output is $\underline{\theta} + \bar{\pi}_{h,l}$. Finally, if $\underline{\theta} < T_2 - k_2$, then both workers put in low effort and line output is $\underline{\theta} + \pi_{l,l}$

Let $\underline{m}$ be the cost of monitoring or mentoring within a network. The high ability worker will be willing to monitor the low ability worker within the same network if $\alpha^{hh}\bar{w}_1 - \underline{m} > \bar{\alpha}^{hl}\tilde{w}_1$. In the presence of social networks, the low ability worker has lower expected wages than the high ability worker though they both put in high effort. This corresponds to higher probability of overtime and or promotions for higher ability workers in these lines. The bigger the difference $\alpha^{hh} - \bar{\alpha}^{hl}$ the stronger are the effects of monitoring or mentoring.

Note that within a network in a line the composition may be one of three types: Both high ability, both low ability or one low and one high ability worker. Assuming that $\bar{\theta} \geq T_1$. Increasing the share of own caste in the first type will have no effect on average output- social networks have no effect when the ability level is high enough that individual wage incentives are profitable for the firm. When both workers have ability below the threshold $\underline{\theta} < T_2$ then again, there are no incentives to monitor the low ability workers and there is no change in individual output. This is because for the mechanism to work, there must be some workers whose productivity is above the threshold where the firm finds it profitable to increase expected wages. Our predictions are therefore: Assume that there is sufficient heterogeneity in worker productivity within a caste group in a line and minimum productivity in the caste group is low, $\underline{\theta} < T_1$. When the share of own network workers in a line increases, the average output of the own caste group increases. This average increase is driven by a larger increase in the productivity of low ability workers.[45] This kind of monitor-

[45]When $T_1 > \underline{\theta} \geq T_2$ then only low ability workers increase effort. If $\underline{\theta} < T_2$, either only low ability worker

ing and reward/punishment schemes depends on the presence of long term repeated relationships which arise when workers are in the same networks.

Summarizing, our main results are (1) as the proportion of own network workers increases, the average productivity within the same network increases but this is driven mainly by an increase in the effort of low ability workers within the network. (2) these effects are stronger, when there are high ability workers in the line who potentially stand to gain a lot in terms of expected wages when joint output increases. Therefore social networks can help improve line output and individual output in lines where the minimum efficiency is very low to begin with, and where the number of same caste-residence network is higher. Moreover it requires the presence of different levels of productivity in the line.

increases effort (due to our assumption that high ability workers gain more from monitoring/mentoring) or both do. Thus overall the low ability worker increases effort for a larger range of parameters.