Essays on social networks, workplace ties and labor productivity

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Contents

List of Tables

List of Figures

Abstract

The role of social contacts in finding jobs, career mobility and other labor market outcomes is well acknowledged both theoretically and empirically in labor economics. The existence of individuals' social networks at their workplace is a pervasive phenomenon, leading to the widespread use of social ties for information, influence and referrals on both sides of the labor market. The central theme of this thesis is to examine the interplay of 'off-workplace socio-economic interdependence' and outcomes at the workplace. Understanding this interdependence has the potential to devise policies which can impact labor productivity, especially in developing countries.

This thesis divided into five chapters, explores the association and mechanisms through which social networks may manifest themselves at workplace and affect workers' behavior. These chapters rely on primary data from the garment manufacturing sector (India), in which the production process takes place in large assembly lines involving strong complementarities in labor input. The first chapter gives the introduction and brief description of the thesis. The second chapter uses high-frequency worker-level panel data from garment factories to find a positive impact of workers' network size on their own and thereby line performance. Our theoretical model and empirical analysis show that monitoring (mentoring) by higher ability types from own social network makes the low-ability type worker put in higher effort, leading to an increase in line output, even in the absence of explicit, individual performance linked incentives. This monitoring (mentoring) takes place through the increased threat of social sanctions arising from the reputation of being a defaulter as own network size in the production line increases. Chapter 3 builds on this context and explores what happens when team performance determines the worker's financial payoff. We use a minimum effort coordination game framework to show that socially connected teams have higher output and better coordination due to a greater degree of pro-social motivations. We test this model's predictions through a unique lab-in-the-field experiment

design that recruited garment factory workers for a real-time effort-based task and shut down other alternative channels. We find that while social incentives augment team productivity, financial incentives may not always give desired results. These two chapters use the familiarity-of-characteristics based network (caste and residential clusters) as a proxy for socio-economic interdependence. Chapter 4, on the other hand, explores actual connections and interaction patterns of the garment factory workers (horizontal and vertical ties), focusing on women, a group that has been historically under-represented at managerial positions. We find that women's personal ties exhibit patterns inimical to career advancement, given the management's dependence on in-house referrals (who are mostly males) for recruitment and promotion. The fifth chapter concludes and summarizes the policy implications. It also discusses future research on social networks and on-the-job outcomes for historically disadvantaged groups (such as women).

The micro-econometric data used in this thesis is unique and innovative in itself (whether from factories or experiment design). Nevertheless, the key findings apply to situations where production occurs in large teams with limited observability of peers' effort. This thesis contributes to the literature on worker incentives, management practices, and firm behavior when workers are complements and informal channels are prevalent for accessing information and influence in the labor market.

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Chapter 1

Introduction

1.1 Motivation

Social networks as social capital is a well-acknowledged fact in a variety of contexts in development economics. Their role in correcting market imperfections due to information asymmetries has gained popularity in labor economics. Both empirical and theoretical literature validate the use of social ties in increasing an individual's probability of obtaining a job. Moreover, theoretical predictions such as reduction in search costs and better screening explain firms' reliance on employee referrals (see Afridi et al. (2015a) for a brief review). Thus, due to widespread use of social ties, existence of one's social network at workplace is quite common.

While it is true that job matches may not be the primary objectives of the formation and maintenance of social networks, their presence at the workplace is bound to influence effort choice and performance through social preferences and prospects of future interactions in a variety of contexts (Leider et al. (2009), Beaman and Magruder (2012)). When workers are socially connected (or unconnected), self-interest also entails elements of collective interests (or discrimination against rival groups) (Basu (2010)).

However, it has also been observed that the structure of social networks and their implications vary across demographic groups - a notion on which there has been limited research in the context of on-the-job outcomes in developing countries (Ioannides and Loury (2004), Afridi et al. (2015a)). The implications of the worker's social networks on their on-the-job outcomes are the central theme of this thesis. In particular, this thesis focuses on the interplay of 'off-workplace socio-economic interdependence' and workplace behavior. In developing countries, where social networks are quite pervasive, the question of how social connections affect productivity is key to the development process (Munshi (2014)).

Empirical evidence on the interaction of social incentives and financial incentives provides mixed evidence (see Ashraf and Bandiera (2018) for a literature review). These studies are mostly based on performance-based payment structures when workers are substitutes (except Hjort (2014) to some extent), and output is observable. The novelty of this thesis is that it looks at the interaction between social incentives and financial incentives when workers are complements in the production process with limited observability of co-worker effort.

Several industries that produce goods for mass consumption (like automobiles, electronic appliances, and apparels) face potential worker moral hazard due to the assembly-line production process (equivalent to a team with Leontief-type-production function). Workers perform pre-determined tasks that are arranged in a specific sequence, and the effort of the least productive worker determines the final output of the line. In this Leontief-type-production arrangement, the management cares about the final output rather than individual output. But given large assembly lines, a competitive product market and minimum wage laws, it is either not possible or profitable to monitor each worker and offer wages according to the individual output. In this setting, the only way team output can increase is if workers coordinate at a higher level of effort. However, if workers expect co-workers to shirk, then their own incentives to shirk increase, leading the entire team into a low effort equilibrium trap. Given that an assembly line arrangement leaves little scope for observability of peers' effort, the latter is more likely to occur, especially when own effort alone cannot raise individual payoff. This thesis attempts to provide useful policy implications based on social incentives that can help organizations augment labor productivity within the assembly-line context.

This thesis uses primary data from garment manufacturing factories located in the industrial hubs of the National Capital Region (NCR), India, to understand the causal links between workers' performance and their social networks. Garment manufacturing takes place in assembly lines that involve the strongest type of complementarities in labor inputs where efforts of the least productive worker determines the line's output. The sample studied in this thesis is representative of labor-intensive garment manufacturing sector of developing countries where men occupy positions of influence (managerial level) and women form the majority of labor-force (blue-collar level).

Additionally, the Indian garment manufacturing sector is amongst the largest providers of employment for low skilled workers offering work opportunities to millions of workers (GOI (2018)). Rural migrants tend to find employment through information about job openings and referrals through their social networks and may also depend on their support to weather socio-economic shocks and risk-sharing.

This thesis is divided into five chapters to analyse the mechanisms through which social networks manifest themselves and affect worker behavior. The first chapter is the introductory chapter providing a brief description of the thesis. Chapter 2 uses high-frequency worker-level panel data from garment factories to find a positive impact of workers' network size on their own and thereby line performance.[1] Our theoretical model and empirical analysis pin down the mechanism through which social networks can affect own labor productivity even in the absence of explicit group based incentives. Chapter 3 builds on this context theoretically and tests predictions through a lab-in-the-field experiment by varying financial incentives.[2] These two

[1]This chapter is joint work with Farzana Afridi (ISI-Delhi) and Amrita Dhillon (King's College London); available online as CEPR Discussion Paper 14687. Refer to Afridi et al. (2020b)

[2]This chapter is joint work with Farzana Afridi (ISI-Delhi), Amrita Dhillon (King's College London) and Sherry Xin Li (University of Arkansas, United States); published version available at `https://www.sciencedirect.com/science/article/abs/pii/S0304387820300201` or refer to Afridi et al. (2020a)

chapters use familiarity based network (caste and residential cluster) as a proxy for socio-economic interdependence. Chapter 4, on the other hand, explores actual connections and interaction patterns of the garment factory workers, focusing on women, a group that has been historically under-represented at the managerial positions. The fifth chapter concludes and makes policy recommendations. Below, I give a brief description of the analysis carried out in the following chapters.

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

Production data from our sample show that the average line productivity can vary by almost 30 percentage points between the least and most productive 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 percentage points less efficient than the most productive worker. However, what also varies is the line composition due to unanticipated absenteeism and attrition of workers. A change in line composition implies changes in the strength of the social networks of the workers and, thereby, social incentives. Workers value these networks because of their importance for providing information and socio-economic support.

Using a moral hazard framework within the given the context, our theoretical model shows that as the size of the network increases, a worker puts in higher effort for given monetary incentives because worker's utility is increasing in the size of her network. However, line output (which is implicitly linked with benefits like higher payoff grade and overtime positions) cannot increase only by the effort of high ability workers; higher effort from low ability type is also required. Thus, high ability types can use the threat of social sanctions to enforce greater effort from the low ability worker. Low ability types put in more effort to avoid the bad reputation of being the one who holds up the line output. The stakes are higher the larger size of own network in the line.

This study combines high-frequency worker productivity data, attendance data and personal information collected through a census of the stitching department in two garment factories, resulting in detailed data on 1744 workers for a panel of 31 production days (giving us 34,641 person-days) to test the mechanism outlined by the moral hazard model. This chapter uses caste networks as a proxy for economic and social interdependence within social networks.[3]

Our identification strategy relies on unanticipated absenteeism and attrition that leads to exogenous variations in network size, which is measured by the share of own caste in the line of worker i on a day. Pearson's χ^2 test validates the independence of caste and line assignment across production days. Using worker-production day level data, individual fixed effects, we observe that individual performance increases significantly with an increase in the caste network size. Line level output also increases as the line becomes more homogeneous.

The least efficient worker drives these results. Socio-economic interdependence within caste networks increases potential costs from loss of reputation for the least efficient workers as network size increases.

Data analysis further provides empirical support for the mechanism argued by our theoretical model. Individual and line productivity increases with the increase in the proportion of job referees and share of the caste of worker i in line l. These results are robust to a host of sensitivity, robustness checks and alternative mechanisms.

The next chapter takes this setting and findings to the lab and examines the interaction between social incentives and financial incentives by making an individual's payoff contingent upon team's output.

[3]Caste, a unique feature of Indian society, is inherited at birth. Using caste networks bypasses the issue of self-selection of an individual to be a member of a network.

1.3 Using Social Connections and Financial Incentives to Solve Coordination Failure: A Quasi-Field Experiment in India's Manufacturing Sector

Productivity data from chapter 2 shows that a production line on an average achieves only around 30% of its target. This chapter solves the puzzle of low coordination equilibrium trap by building on the factory data findings and varying financial payoffs.

First, this chapter analyses coordination failure theoretically using a one-shot minimum-effort game where workers choose their effort levels to maximize their payoffs. With no observability of effort, no communication, no differences in ability distribution across teams, and using the salient characteristic of social networks that the 'degree of pro-social motivation' towards other team members is higher in socially connected teams, the model makes three predictions:

1. Socially connected groups coordinate on a higher group output on average (across all possible ability matches) than unconnected groups. The individual output is higher on average in connected groups, but only for low ability workers.

2. Wasted output is lower on average (across all possible ability matches) in connected groups than unconnected groups.

3. A discrete lump sum bonus given above a threshold level of output will increase the output of groups/individuals who were producing below T before bonus, if it is sufficiently large relative to the marginal cost of effort. If the threshold creates a focal point, it implies, in addition, that it leads to an increase (decrease) in the output of those groups/individuals who were producing below (above) T to begin with.

We check these predictions by setting up a unique real effort based task in a lab-in-the-field experiment in the industrial hub of Delhi identified from chapter 2. Participants were invited through pamphlet distribution in the catchment areas observed from the factory workers data discussed in chapter 2 (N=268 subjects). They were randomly assigned to two types of teams of size four (same gender) - (i) socially connected (workers belonged to the same caste and residential clusters; 33 sessions) and (ii) social unconnected (workers belonging to different caste and different residential clusters; 34 sessions).

Replicating the assembly line set up, each worker was assigned specific color beads at a separate workstation to prepare the beaded strings of 20 cm each in 10 minutes. Assembling these four colored strings (one of each color) would form one bracelet (the team output). Along with Rs.200 as the fixed participation fees, payment was based on a piece-rate system, i.e., every additional bracelet completed by the team fetched Rs.100 per individual. The experiment included elaborate explanations regarding the payoffs and the task. Before the start of the task, the experimenter announced workers' full names with titles and residential clusters to prime social connectedness.

With no communication, no observability of effort, and the assurance of keeping the information of individual output private, the experiment design tried to pin down the impact of pro-social motivations. An entire session lasted for 45 minutes that included filling up a post-experiment questionnaire, followed by calculation of team output in front of the participants. The lowest number of colored strings determined the final payoff without revealing each subject's performance.

This study also experimented with lumpsum bonus payoff – 'bonus with gains framing' and 'bonus with loss framing' that guaranteed an additional lump-sum amount of Rs.150 per team member if entire team crossed the threshold of 5 bracelets along with piece-rate payoffs .[4]

Using OLS estimation, the data analysis shows higher team output and better coordination (i.e, lesser wasted effort and with-in group dispersion) in socially connected teams. Introducing a lumpsum bonus, on average, does not enhance the advantage that the socially connected have over the socially unconnected groups since it

[4]Threshold of five bracelets was decided on the basis of piece-rate based sessions where median was four bracelets.

creates a focal point for all workers to coordinate on. Breaking down the sample into groups of individuals and teams – (i) those producing above five bracelets, (ii) below 5 bracelets, we observe that the bonus can serve as a double-edged sword – increasing the productivity of less productive workers/groups but lowering the productivity of those producing above the threshold. Therefore, a bonus is likely to reduce variation in productivity across teams but will only lead to higher overall firm output if it is aimed sufficiently high.

As predicted by our model, higher levels of pro-social motivation between co-workers in socially connected teams explain these findings. Further analysis of the post-experiment survey data provides additional evidence on the mechanism. These results are robust to a host of sensitivity checks and alternative mechanisms.

One must note that we use data of male subjects to test the theoretical predictions. Due to severe mobility restrictions and patrilineal social arrangements, experimenters faced logistics challenges recruiting and priming women subjects according to the experiment design. Women came to participate in experiments only if they could find friends to accompany them, increasing the probability of knowing someone in socially unconnected teams. Also, mixed-gender sessions suffer from power issues due to limited participation by women. This *suggests* that cultural barriers affect the objectives and structure of women's ties differentially than men and need more in-depth examination if we are to understand the implications of social connections for women in manufacturing.

Another parallel observation from the factory data (chapter 2) is that women are over-represented in low-paying and low-skilled jobs and under-represented in managerial positions, much like other manufacturing sectors in most developing countries (ILO (2017)).[5]

Given the importance of employee referrals in the garment manufacturing sector (Heath (2018)), I examine the structure and patterns of workplace networks of garment factory workers in chapter 4. Since workplace ties contain possible resources

[5] E.g., food processing, construction, skilled agriculture, textiles, etc.;source: https://qz.com/india/1404730/the-shocking-gap-between-indias-male-and-female-workers/

that can aid in career advancement, it is of practical importance to explore the structure and pattern of workers' personal ties.

1.4 Workplace Ties: A Case Study of Women in Indian Garment Manufacturing

Workplace literature shows that certain groups, such as women face disadvantages when informal channels such as referrals are important sources of accessing information and resources. These groups may get excluded or may exclude themselves from useful interactions and thus face "informal barriers" in career advancement. These findings come from white-collar job settings of the developed countries.

This study is the first to examine workplace ties of blue-collar workers in a developing country context where women face cultural barriers regarding cross-gender interactions and physical mobility. This analysis is not only critical from the perspective of gender inequality but also from the need to address the structural changes that garment manufacturing sector is going through in developing countries.[6]

This chapter looks at the personal networks of 1744 blue-collar workers at the factory while controlling for any variation in interpersonal characteristics and workplace constraints (or opportunities). It specifically focuses on the objectives of forming personal ties and interactions with supervisors, who are potential referees for promotions, at the workplace.

Data analysis shows significant differences in personal network composition by gender. Women's personal networks are smaller, clustered within their functional units and more homogeneous than men's personal networks. While supervisors do not figure in personal networks of either gender, women are significantly less likely to mobilize interactions with supervisors for professional or personal purposes. Thus, women's personal ties at the workplace exhibit patterns that are opposite of those identified by existing literature as instrumental for career advancement. The emerg-

[6] https://voxdev.org/topic/firms-trade/\breaking-gender-barriers-how-women-are-becoming-managers

ing patterns *suggest* that the reliance of managements on employee referrals can be inimical to women's career mobility.

However, data shows no gender differences when the purpose of a tie is to provide 'companionship'. Additionally, data shows similar workplace network patterns if women mobilized ties for current job information or are married. These factors might have helped women overcome cultural barriers and mitigate safety concerns through companionship or shift in aspirations. These findings underline the relevance of research that focuses on cultural barriers and implications of social ties on female labor force participation.

The key findings in this thesis speak to multiple strands of literature on worker incentives as well as to existing research on management practices and firm behavior as outlined in chapter 5. We postulate that managements should consider the role of social incentives (thereby, social networks) while designing worker incentives to improve productivity and performance. Even though this thesis focuses on garment manufacturing, the results are applicable to situations where the production process is organized into teams with fixed, individual wages, limited observability of peer performance and prevalence of informal channels for accessing information in the labor market.

Chapter 2

The Ties That Bind Us: Social Networks and Productivity in the Factory[1]

2.1 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.[2] In our setting of the labor intensive garment industry in India, average team productivity can vary by almost 30 percentage points 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 percentage points less efficient than the most productive worker.

[1]This paper is joint work with Farzana Afridi (ISI-Delhi) and Amrita Dhillon (King's College London); available online as working draft. Refer to Afridi et al. (2020b).

[2]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.

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 complementarities 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.

2.1.1 Main results

Our findings suggest that a 1 percentage point increase in the strength of the workers' social network - the proportion of workers belonging to own caste - in the line on a day, raises workers' own productivity by more than 10 percentage points. 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 15 percentage points while the average line performance improves by more than 23 percentage points 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 seasonal trends in production in the industry and at the line level.

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 of obtaining the limited overtime positions and also of being promoted to higher grades due to recommendations by the line supervisor. Since the line supervisor cares about 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 the output.

Results suggest that this 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.[3] 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 (Hal (1990), Ghatak and Guinnane (1999), Bryan et al. (2015)), Heath (2018), Dhillon et al. (2019)).

These 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 this analysis is based on garment factory production lines, it is applicable to situ-

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

ations 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 even in the absence of monetary benefits for improving individual or group productivity. The results of our analysis indicate that identifying workers who are widely connected to co-workers through job referrals or residential location could carry implications for productivity through the optimal design of production schedules and composition of teams in the firm.

2.1.2 Literature review

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)).[4]

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 worker performance is contingent on the nature of financial incentives (Hjort (2014), Kato and Shu (2016)).[5]

While all of the above research focuses on workers as substitutes in the production process, workers' own productivity may not be influenced by co-worker perfor-

[4]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.

[5]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 the production process was sequential, 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.

mance either through a desire to conform to a social norm (e.g. peer pressure or local average network effect) or through strategic complementarities (e.g. knowledge spillovers or local aggregate network effects) when workers are complementary in the production process and observability of effort is imperfect as in the production lines in garment manufacturing. This study, thus, extends the broader literature on the role of social networks in job search to its impact on worker and firm productivity.

The remainder of the chapter is organized as follows. Section (2.2) describes the background of our study, including the production process and worker incentives in garment factories. Section (2.3) summarizes the observed data regularities. Section (2.4) provides the theoretical framework. We discuss our empirical methodology, report the results of our analysis in Section (2.5) and conduct robustness checks in Section (2.6). We underscore the mechanism that explains our findings in Section (2.7) and conclude in Section (2.8).

2.2 Background

2.2.1 Caste as a proxy for social networks

Workers' social networks play a significant role in the functioning of labor markets (Afridi et al. (2015a)) and in ensuring migrants' economic mobility, more so in low income countries (Munshi (2014), Munshi (2019)). Historical data highlights 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 ur-

[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.

ban areas, particularly amongst rural migrants in the city's working-class neighborhoods.[7]

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 from the same factory as our survey respondent, 42% of workers were referred to the management by the informant and 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 residence information being available for a worker in our data). Thus, own-caste neighborhoods represent the social networks that workers derive economic benefits from.

Additionally, anthropological literature tracing the evolution of migrant labor force in the urban industrial hubs has emphasized the importance employers across India gave to recruitments through the contacts of their existing employees. This led to the further strengthening of labor markets along the lines of caste (also kinship and new urban neighborhoods) (Morris (1965), Holmstrom (1984)). To quote Holmstrom

[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)).

[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.

(1984) "...employers relied excessively on the existing employees for recommendation of new workers that led to clusters of people from same caste or area (and possibly relatives) to be concentrated into a particular industry. This increased the dependence of a worker on the firm and helped management to keep strikes at bay, resulting in a more stable workforce, controlled absenteeism and turnover rates..." (pp. 202, 218, 219(ibid)). Morris (1965) studying the Bombay cotton mills labor force documents that absenteeism was quite low in this sector (according to him overestimated by the employers), and high turnover rates only reflected movement within the mills.

2.2.2 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 single factory can have multiple production or stitching floors. On each floor there are multiple production lines in which stitching machines are placed one behind the other (see Figure 2A.1 in Appendix 2.A). Besides the machine operator who is responsible for stitching, the production line also consists of helpers (to fold, cut, match or iron different parts of garments) who assist operators. Henceforth, we will use the term 'worker' to denote operators and helpers who contribute to stitching of the garment. Each line is assigned a particular style of garment to be produced over a day or several days until the production target for that garment-style is met.

There are two types of production lines: assembly and non-assembly lines. 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 begins at the back of the line and at the front of the line the stitched garment is assembled.[9] 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

[9] Figure 2A.2, Appendix 2.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.

the least efficient worker.[10]

Observability of co-worker effort is imperfect due to differences in operations performed by workers in an assembly line (33, on average, in our data). However, as can be seen from Figure 2A.1, workers can see who is sitting in their line even though they cannot directly observe each other's output. Moreover, upstream workers would be aware of where production bottlenecks exist downstream. 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. 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.[11] 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.

Supervisors allot limited overtime positions to workers, which typically pay an hourly wage higher than minimum wages. Workers total earnings, therefore, would depend on their fixed grade pay and overtime wages. Since overtime positions are few, more productive workers have a higher probability of receiving over time work. They also have a greater chance of being promoted to higher grades. The management maintains records of operational efficiency for each operation (but not worker), so the

[10]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.

[11]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.

supervisor would know which operations are holding up the line output. Although workers are unlikely to be punished due to limited liability (minimum wage) constraints, the supervisor would likely know who is the weak link within an operation or in the line. In essence, therefore, there exist implicit individual financial incentives linked to being a more productive worker. Given the production externalities in the assembly line, the performance of co-workers in an assembly line can 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)).[12] 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.[13] 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.

[12] Average 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 or 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.

[13] Adhvaryu et al. (2019) document the virtual absence of relational trading between supervisors inside garment factories to reallocate workers in order to address worker absenteeism.

2.3 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.

2.3.1 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 includes all workers and supervisors in the stitching department of the sampled factories.[14] The workers' survey gathered information on individual demographic characteristics, including native state of residence and caste, years of experience in the garment industry, the process of obtaining the current job particularly referrals, worker-supervisor and co-worker relationships. We conducted a shorter survey of supervisor characteristics, including demographics, work experience and the process of obtaining the current job.

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. areas are often classified as *harijan* or low caste) or in fostering shared experiences. Narrow

[14]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.

caste categories, viz. *jati*, on the other hand, represent identity concerns, which is not the focus of this paper.

2.3.2 Worker productivity and attendance data

Since the factory managements were recording line level productivity only by operation, we designed a protocol for collecting hourly, worker level output, and line composition that mapped workers to an operation within each line. These data were obtained for a period of 31 working days between September-October 2015, a sub-set of the 61 days during which the worker census was conducted.[15]

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.[16] 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.[17] Each worker's efficiency, therefore, is measured as follows:

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

[15]Every production line has a 'feeder' assigned to it whose job is to note down productivity by operation in a line each hour. Using our data collection protocol, the 'feeder' also noted the name and unique ID of the worker at each operation in the line. This allowed us to obtain disaggregated worker level output, and also follow workers across lines over the 31 day period.

[16]The SAM is the time it takes in minutes to conduct a particular operation under ideal conditions. The SAM, thus, is higher for more complex operations. Using the SAM for the style-operation, we can calculate the target output per worker per style operation. Note that the SAM measure does not take into account that workers may get tired in later hours or bottlenecks may arise (Adhvaryu et al. (2019)).

[17]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.

the assembly line. Data on workers' and supervisors' daily attendance was obtained from the Human Resource (HR) departments of the two factories.[18] 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.[19]

Table 2.1, 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.[20] The same worker characteristics are described by their caste category in columns 2-4 in Table 2.1. 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 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 .[21]

[18]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 are 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. Workers could leave (or enter) the factory only on showing their IDs cards enabling HR to keep track of half day leaves as well.

[19]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 2A.1 in Appendix 2.10 for details.

[20]Supervisors had, on average, 13 years of experience in this sector and about 72% came to know about the current job through informal sources. There were no female supervisors despite the majority of workers being women. Majority of supervisors were from M category unlike workers who were more likely to belong to H category. Almost 23% 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.

[21]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)

Table 2.2, 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. Note that worker efficiency is not statistically significantly different across caste categories. The average network strength, measured by the 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 2.1 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 of a line 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 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. 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 2.2.b traces the average efficiency of a line across workdays, which can be seen to vary by more than 25 percentage points. 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 H caste

are insignificant, thus, validating the claim that productivity is not systematically correlated with caste groups.

workers in a line across work days can vary by up to 22 percentage points, 12 and 18 percentage points for the M and L caste categories, respectively.[22] As discussed in the section 2.5, neither worker productivity nor absenteeism rates differ significantly across caste groups in our sample.[23]

We correlate the caste composition of the assembly line, worker and line level productivity in Figure 2.3 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.

In the following section we lay out a theoretical framework for understanding the potential role of social networks on worker productivity.

2.4 Theoretical Framework

The above discussions highlight the fact that 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. We build on the insights from the microfinance literature (Hal (1990), Ghatak and Guinnane (1999), Bryan et al. (2015)) and applications in labor economics (Heath (2018), Dhillon et al. (2019), Pallais and Sands (2016)) to theoretically demonstrate how social networks can solve moral hazard/adverse selection problems when formal institutions cannot, in a context where workers are complementary in the production process.

Simply put, when workers have to be paid minimum wages, it creates a limited liability constraint for firms, which in turn implies that to motivate workers the rewards

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

[23]Since workers in our study come from approximately 300 districts across 16 states, the likelihood of workers of same sub-caste or *jati* sitting in a particular line on a day is negligible. Hence we don't use *jati* to categorize workers.

for high effort have to be correspondingly higher. When there is a high degree of complementarity in the production function the firm gains more from inducing greater effort from all workers as this leads to disproportionately larger expected output than from inducing only a few workers to put in high effort. But since the minimum wage constraints push up the cost of performance based pay, the firm instead may decide to go in for lower powered incentives or no incentives at all.[24] In our context, by aligning the incentives of the high ability line supervisors to the line output, the management creates implicit team incentives for workers not only to put in more effort themselves but also to induce other co-workers to put in higher effort. Thus when a production team is large, workers' social networks can be leveraged to provide network based rewards and punishments to support the firm's own implicit incentives.

Formally, suppose there are two workers in the firm (the model is easily generalized to more workers) characterized by their observable ability types $\theta_i \in \{\bar{\theta}, \underline{\theta}\}$.[25] Output of worker i is increasing in θ and effort. For simplicity we assume the production function is given by $y_i = \theta + X$, where X is a random variable that takes one of the values $\{x_1, x_2\}$ with $x_1 > x_2$. Workers choose from two levels of effort $e_i \in \{h, l\}$ with $h > l$. Low effort has zero cost while high effort costs c. 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 $\pi_{h,h} = \alpha^{hh} x_1 + (1 - \alpha^{hh}) x_2$. If only one worker chooses high effort the expected output is $\pi_{h,l} = \alpha^{hl} x_1 + (1 - \alpha^{hl}) x_2$. 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. 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 $(\pi_{h,l} | \theta_i = \bar{\theta}, \theta_j = \underline{\theta}) > (\pi_{h,l} | \theta_i = \underline{\theta}, \theta_j = \bar{\theta})$. 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 $\pi_{h,h} > \pi_{h,l} > \pi_{l,l}$ and complementarity in effort levels implies that $\pi_{h,h} - \pi_{h,l} > \pi_{h,l} - \pi_{l,l}$. Thus α^{e_i, e_j} must satisfy: $\alpha^{hh} > \alpha^{h,l} > \alpha^{ll}$ and $\alpha^{hh} - \alpha^{h,l} > \alpha^{h,l} - \alpha^{ll}$.

Since effort is imperfectly observed or, equivalently, is non-verifiable, the firm

[24]Due to stiff product market competition in the garment industry there is also an upper bound on product prices (given by a zero profit condition) so that performance based wages cannot be recouped if worker ability is too low.

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

faces moral hazard. To induce workers to work harder the firm can offer incentive compatible contracts, such that wages are conditioned on individual output - w_1, w_2. Firms can commit to their wage contracts and there is a minimum wage of $\underline{w}$ in the industry. Workers are risk neutral.

2.4.1 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:

$$u_i(e_i, e_j) = E(w|e_i, e_j) - c \tag{2.1}$$

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. Details are in Appendix 2.B. Below, we assume (w.l.o.g) that when the firm induces the same level of effort in each ability type of worker, it pays the same wages.

Case 1: The per worker expected profit of the firm 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)

$$\theta + E(\pi(e_h, e_h)) = \pi_{h,h} - \alpha^{hh} w_1 + (1-\alpha^{hh})w_2 \tag{2.2}$$

subject to the participation constraints (PC), the incentive compatibility (IC) constraints and a limited liability (LL) constraint.

(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:

$$\alpha^{hh} w_1 + (1-\alpha^{hh})w_2 - c \geq \underline{w} \tag{2.3}$$

(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 that high effort is a dominant strategy for worker i: IC(1) (given worker j puts in high effort):

$$\alpha^{hh}w_1 + (1-\alpha^{hh})w_2 - c \geq \alpha^{lh}w_1 + (1-\alpha^{lh})w_2 \tag{2.4}$$

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

$$\alpha^{hl}w_1 + (1-\alpha^{hl})w_2 - c \geq \alpha^{ll}w_1 + (1-\alpha^{ll})w_2 \tag{2.5}$$

and (3) the LL constraint: $w_1, w_2, w_3 \geq \underline{w}$. Denote average ability as $\mu = \frac{\theta+\bar{\theta}}{2}$. Using the solution to this problem (see Appendix 2.B), expected profits per worker are: $E(\pi(e_h, e_h)) = \mu + \pi_{h,h} - \alpha^{hh}(\underline{w} + \frac{c}{\alpha^{hl}-\alpha^{ll}} - (1-\alpha^{hh})\underline{w}$.

Case 2: Alternately, the firm can induce high effort only from one worker. Since ability is assumed to be observable, the firm would find it profitable to pay higher wages to induce high effort from the high ability worker and induce low effort (and pay minimum wages) from the low ability worker (given our assumption that $\pi_{h,l}$ is higher when the high ability worker puts in high effort than when the low ability worker puts in high effort). The maximization problem has the same structure as (2.2). Expected profits per worker are now $\mu + \pi_{h,l} - \frac{\alpha^{hl}}{2}(\frac{c}{\alpha^{hl}-\alpha^{ll}}) - \underline{w}$ (see Appendix 2.B for details).

Case 3: 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 per worker are $\mu + \pi_{ll} - \underline{w}$.

What effort profile will the firm induce out of cases (1)-(3)? Let $T_1 \equiv \frac{2\alpha^{hh}-\alpha^{hl}}{2(\alpha^{hh}-\alpha^{hl})}\frac{c}{\alpha^{hl}-\alpha^{ll}}$ and $T_2 \equiv \frac{\alpha^{hh}}{\alpha^{hh}-\alpha^{ll}}\frac{c}{\alpha^{hl}-\alpha^{ll}}$. The firm induces high effort from both workers iff expected profits are higher in case (1) as compared to both cases (2) and (3). Expected profits in case (1) are higher than expected profits in cases (2) and (3) iff $x_1 - x_2 \geq max(T_1, T_2)$. Intuitively, the firm will induce high effort in both workers only if the marginal gains from doing so for each worker, $x_1 - x_2$, are higher than the marginal cost or higher expected wages that have to be paid, which is $\max(T_1, T_2)$, depending on which of the other options is more profitable.

The key point is that, in the absence of benefits from social networks, both types of workers get higher expected wages when the firm induces high effort than when the firm induces high effort in only one worker or does not induce high effort at all.

2.4.2 With social networks

Social networks can be leveraged to provide monitoring or social collateral when team incentives are involved. Thus, networks can help to reduce the wages that must be paid by the firm to workers to reward them for higher effort, increasing the profitability of inducing high effort.

Assume that the per worker costs of enforcing contracts using collective rewards and punishments by the network are sufficiently small. There is an exogenous probability of separation from the firm $1-\gamma$. Separated workers rely on their social networks 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 of coworkers in the social network of worker i of caste k. 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 the better is information transmission on worker i to others in the network but outside the team. Suppose the firm wishes to induce high effort in both workers. The utility function with networks is:

$$u_i(e_i, e_i)_i^k = \gamma(E(w|e_h, e_h) - c(\theta)) + (1-\gamma)V(f_i^k|e_i) \tag{2.6}$$

Note that $V(f_i^k|l) = \underline{V} < V(f_i^k|h)$. We can re-write the constraints for the maximization problem of the firm, (2.2) as follows:

(1) the PCs:

$$\gamma(E(w|e_h, e_h) - c) + (1-\gamma)V(f_i^k|h) \geq \gamma\underline{w} + (1-\gamma)\underline{V} \tag{2.7}$$

(2) The ICs:

$$\gamma(E(w|h,h) - c) + (1-\gamma)V(f_i^k|h) \geq \gamma(E(w|l,h)) + (1-\gamma)\underline{V} \tag{2.8}$$

and

$$\gamma(E(w|h,l) - c) + (1-\gamma)V(f_i^k|h) \geq \gamma(E(w|l,l)) + (1-\gamma)\underline{V} \tag{2.9}$$

and (3) the LL constraint: $w_1, w_2, w_3 \geq \underline{w}$

Denote $\frac{1-\gamma}{\gamma}(V(f_i^k|h) - \underline{V}) = K$. Suppose the firm wants to induce low effort by both workers. There are no incentive constraints. Since $V(f_i^k|l) = \underline{V}$ the wages that satisfy the participation constraint are $w_1 = w_2 = \underline{w}$. Below we assume $c > K$ to ensure that the bonus for high effort is positive.

Let $\tilde{T}_1 \equiv \frac{2\alpha^{hh}-\alpha^{hl}}{2(\alpha^{hh}-\alpha^{hl})}\frac{c-K}{\alpha^{hl}-\alpha^{ll}}$ and $\tilde{T}_2 \equiv \frac{\alpha^{hh}}{\alpha^{hh}-\alpha^{ll}}\frac{c-K}{\alpha^{hl}-\alpha^{ll}}$. In the analysis without social networks, we saw that if $x_1 - x_2 < \max(T_1, T_2)$ then the firm would not induce high effort in both workers (Proposition (1) in the Appendix 2.B). Proposition (2) in Appendix 2.B shows, however, that it may be possible to induce high effort in both workers when social networks can ensure that K, the network rewards for high effort, are sufficiently high. For simplicity, suppose that the degree of complementarity is high then the binding constraint is T_1 without networks and $\tilde{T}_1$ with networks. The firm cannot induce high effort in both workers without the power of social networks, e.g. if $\tilde{T}_1 \leq x_1 - x_2 < T_1$. Similarly, if the binding constraint is T_2 without networks and $\tilde{T}_2$ with networks, then the firm cannot induce high effort in both workers without networks but can do so with networks under the condition $\tilde{T}_2 \leq x_1 - x_2 < T_2$. Moreover, as f_i^k increases, the wages needed to reward worker i for high effort will decrease, therefore for any given expected monetary incentives (such as overtime bonus or promotions), worker i puts in higher effort.

Overall, our theoretical analysis suggests that less able workers are more likely to be holding up wages of the high ability workers due to low assembly line output.

However, when the social network size in the line increases it leads to higher effort by low ability workers for the same fixed wages, but coupled with greater chances of getting overtime or promotions. High ability workers will then increase effort in response to the rise in potential expected wages they can get from the supervisor. The key part of our theory is that due to complementarities in production, high ability workers have strong incentives to enforce greater effort from low ability workers using social network rewards or punishments. By themselves, high ability workers cannot increase line level output and therefore the probability of getting higher expected wages from the firm.[26] Thus, the effort level of high ability workers responds less to an increase in monitoring by the network while it responds more for precisely those workers who might be holding up line output.[27] As the number of such potential enforcers/monitors/informants (to other network members outside the line) in the line increases, low ability workers increase their effort correspondingly.

2.5 Methodology and Results

2.5.1 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

[26]Note that assuming $c > K$, expected wages are higher when both workers put in high effort than when only the high ability worker puts in high effort.

[27]Note that when complementarities are sufficiently strong, i.e. $T_1 > T_2$ then high ability workers start from a higher wage and higher productivity level than low ability workers, so as a percentage of initial output, responsiveness is higher for the low ability workers. But within line variance is unaffected.

market), the scope for being able to selectively choose workers is limited.[28]

To test our claim that the caste of a worker and worker assignment to a line 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 assigned to line L, then $P(C_i \cap L_i)$ is the joint probability of worker in caste C being assigned to 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 2A.2 in Appendix 2.10 gives a snapshot of the caste distribution of workers in production lines on a randomly selected work day for the export factory and Table 2A.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. 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.[29]

2.5.2 Estimation methodology

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

$$\mathrm{Y}_{ilt} = \alpha + \beta network\_strength_{ilt} + \gamma \mathrm{X}_i + \epsilon_{ilt} \tag{2.10}$$

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* worker's caste category (H, M or L) divided by the total number of workers in the line on that

[28]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.

[29]In addition to the above test, we have shown previously that worker productivity does not vary systematically by caste. We also find that worker absenteeism is not systematically correlated with caste categories (Table 2A.4 in Appendix 2.10).

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. Standard errors are clustered at the factory-line level. β is our main coefficient of interest. If $\beta > 0$ 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 (2.10) 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 in subsequent specifications, besides factory floor and line fixed effects to account for floor and line level unobservables (e.g. floor managers' and line supervisors' characteristics).[30]

To analyze line level productivity we estimate equation (2.10) 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 (2.10), as controls. In subsequent, stricter specifications, we include floor and line fixed effects to control for time invariant, line level unobservables.[31] The standard errors are clustered at factory-line level, as in the individual level analysis.

[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 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.

2.5.3 Results

Line composition and worker performance

The results of the analysis using equation (2.10) are presented in Table 2.3. In columns 1-4 we conduct the analysis for all production lines - assembly and non-assembly. Column (1) shows estimates of equation (2.10), where 'Network strength' is as defined in equation (2.10). The coefficient β is positive, suggesting that a one percentage point increase in the proportion of workers of one's own caste increases, albeit insignificantly, an individual worker's efficiency by 6.7 percentage points. In column 2 we include individual fixed effects. The coefficient of interest is now not only significant at the 5% level, it is also larger in magnitude. A percentage point increase in the proportion of workers who are own caste in the line raises individual productivity by more than 10 percentage points. In subsequent columns we include floor (column 3) and line (column 4) fixed effects. The magnitude and significance of the estimate is robust.

To elaborate on what this estimate implies, 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 percentage points in her daily efficiency implies that her daily output increases by 64 pieces or, on average, 8 additional stitched pieces per hour when the number of own caste workers increases by about half (i.e. about 1 percentage point in an average line of 33 workers with equally distributed H, M and L caste.). Since the mean worker efficiency is 31% the estimates in columns (2) - (3) suggest that worker efficiency can rise by approximately 30.6 - 33.2% when a worker is more socially connected within her line. While these effects may seem large, note that the the base is very low (average worker productivity is 0.3) implying large increases in percentage point terms.

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 columns (5) - (8). The coefficient β is somewhat stronger, suggesting 34.2 to 37.7% higher worker efficiency when the proportion of own caste workers in the line rises by 1 percentage points. This also suggests that the overall effects we observe in columns 1-4 are driven by assembly lines.

Line composition and line performance

In Table 2.4 and Table 2.5 we estimate the minimum and average line efficiency, respectively, using equation (2.10) for all lines and assembly lines, as in the worker level analysis in Table 2.3. In Table 2.4, column 1 we include only line level characteristics as controls. A one percentage point increase in the network strength as measured by the CCI causes a 11.3 percentage point increase in the line's minimum efficiency. Augmenting the specification with floor fixed effects increases the point estimate to 12.1 percentage points and to 15.8 percentage points when we address line level heterogeneity. Restricting the sample to assembly lines alone 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 fixed effects, the results suggest that the minimum efficiency of the line or the least productive worker's performance increases by 316% when more workers in the line belong to the same caste-based social network.

In Table 2.5 we show the results of the same analysis but when the dependent variable is the average efficiency of the line. Columns 1- 3 indicate a 22 to 24.7 percentage point improvement in a line's average efficiency when the caste composition of the line is more homogeneous. We restrict the sample to only assembly lines and redo the analysis in columns 4-6. The sample size falls from 1043 to 868 but the point estimates are similar to the ones obtained from the entire sample in columns 1-3. Our preferred specification with line fixed effects suggests 78.3 - 122% higher average efficiency when the line's network strength increases by 1%.

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. The estimated effect sizes are plausible since the supervisor's bonus increases non-linearly with higher line efficiency thresholds as discussed in Section 2.3. 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. In the following section we also show that the impact on minimum efficiency in a line is more robust.[32]

2.6 Robustness

2.6.1 Sample selection

A simple *t*-test for those workers who have lower vis-a-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 2A.4, there is no systematic relationship between caste category and worker presence, but experienced workers are more likely to be observed working.[33]

Suppose, however, that more productive workers replace the less productive, absent workers in a line on a day, and this is systematically correlated with the caste composition of co-workers in a line. We adopt a non-parametric method to check the

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

[33]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.

robustness of our results in Table 2.6 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. Using the inverse of predicted probability of being present, we re-run the worker level analysis in Table 2.6. Columns 1-3 report the original, unweighted estimates while columns 4-6 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.

2.6.2 Trends

As we mentioned previously, demand can vary over time (due to seasonal changes, festivals etc.) 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. In Table 2A.5 we report the results of the analysis with month of production and line specific month of production fixed effects. Our results are robust to secular and line specific trends except in column 6 when the outcome is the average efficiency of the line. The impact of network strength on average efficiency is, however, marginally significant ($p<0.10$) when we restrict the sample to only assembly lines. Note that our measure of efficiency accounts for any changes in production style. Nevertheless, we check the robustness of our estimates to trends at the production week level as well as production style fixed effects. The results are unchanged.

2.6.3 Number of clusters

Another concern with our estimates is that high intra-cluster correlation, coupled with the small number of clusters (production lines) in our study, would lead to incorrect standard errors. Although we have addressed the possibility of high intra-cluster correlation by clustering our standard errors at the line level, the presumption that these standard errors are correct is based on having a large number of clusters. 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 2.7. Columns 1-2 report pair-wise bootstrapped standard errors, with and without line fixed effects, respectively. In columns 3 and 5 we report the pair-wise bootstrap standard errors and use the cluster-bootstrap procedure proposed by Cameron et al. (2008) in columns 4 and 5. Our standard errors are marginally higher but the main coefficient of interest remains significant, consistent with results reported in Tables 2.3-2.5.[34]

2.7 Mechanism

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 (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 2.8 (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 2.8, 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

[34]We also drop outlier observations, i.e. those line-days (not the entire day) whose worker strength falls in the lowest one percentile of the distribution of strength and those days on which number of factory lines is less than 30. From 1043 line-days we end up with 972 line-days. We then wild-cluster bootstrap our standard errors, which gives the same conclusions as in Table 2.4 and Table 2.5.

co-reside in the line, as shown in Panel C of Table 2.8, 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 (2.2.2). 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 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 worker's efficiency is larger for least performing worker (16 percentage points) as compared to the average productivity worker (10 percentage points). 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.[35]

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'. If the reputation mechanism is valid then we should see a significant positive coefficient on this interaction term. Our results suggest exactly that. In columns 1 and 2 in Table 2.9, we find that almost all of the effect of network strength can be explained by its interaction with informant presence in factory. In columns 3 and 4, for line level analysis, we find a negative albeit insignificant effect of informant presence on the line's average (column 3) or minimum (column 4) efficiency, but a positive (insignificant) effect of the interaction term. The total effect of informant presence is significant in column 3 ($p<0.10$) and only marginally insignificant in column 4.[36]

[35] 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.

[36] 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 in our sample) and 0 otherwise. We find that coefficient on the interaction term of this dummy with the network strength is insignificant, as shown in Table 2A.6. Thus those attending work for fewer days do not respond significantly differently to the network strength from

Knowledge spillovers through (non-network) peer effects is likely when co-workers can observe each other's effort or output, are performing similar 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 when we restrict our sample to only assembly lines in Tables 2.3-2.5, the coefficient on network strength is more robust, suggesting 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 2A.7, Appendix 2.10), 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.

We might expect that conformism to an efficiency norm or altruism towards low productivity workers in the network may lower the line level variance in individual output (if high ability workers incur costs to own efficiency when spending time helping others). But we do not find any significant impact of network strength on within line variation in worker efficiency (Table 2A.8, Appendix 2.10), using equation (2.10), which should fall if these mechanisms are at play.[37] Hence explanations which suggest a fall in variance in efficiency within a line such as adherence to a common norm and altruism, are unlikely.[38] We conclude that economic interdependence within one's so-

those who attend more often. This suggests that social networks impact workers irrespective of the number of days they interact with each other within the factory.

[37]The effect on the minimum efficiency worker is not accompanied by *all* low ability workers choosing to work harder when facing an increase in own caste proportion, nor do we find any significant results on higher ability workers responses to higher network strength in the line. We also do not find any change in variance in efficiency of workers of the same a caste in a line when that group's network strength increases.

[38]Caste may be perceived as an identity rather than a network, making taste based discrimination

cial network creates incentives for workers to put in greater effort when the presence of co-workers within the network in the team is larger.

2.8 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 in competitive product markets, workers' social networks can be leveraged to improve efficiency in the absence of high-powered performance based incentives.

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 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.

a possible explanation of our findings. We argued in Section 2.3 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* in a line on a workday.

2.9 Tables

Table 2.1: Worker characteristics

		Caste Category		
Characteristics	**All** N=1744	**L** N=384	**M** N=543	**H** 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. Standard errors in parentheses.

Table 2.2: 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 2.3: Worker performance and line composition

	Worker efficiency							
	All lines				*Assembly lines*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network strength (β)	0.067	0.103**	0.103**	0.095**	0.105**	0.117**	0.116**	0.106**
	(0.045)	(0.047)	(0.046)	(0.045)	(0.046)	(0.052)	(0.051)	(0.050)
Constant	0.254***	0.276***	0.259***	0.328***	0.278***	0.279***	0.262***	0.333***
	(0.031)	(0.019)	(0.075)	(0.071)	(0.031)	(0.020)	(0.080)	(0.076)
Individual fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Floor fixed effects	No	No	Yes	No	No	No	Yes	No
Line fixed effects	No	No	No	Yes	No	No	No	Yes
Number of observations	34,641	34,641	34,641	34,641	32,176	32,176	32,176	32,176
Number of workers	1744	1744	1744	1744	1633	1633	1633	1633
Number of lines	37	37	37	37	31	31	31	31
R-square	0.010	0.550	0.550	0.555	0.011	0.546	0.546	0.550

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. Robust standard errors clustered at the line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 2.4: Line performance and composition

	Minimum Worker efficiency					
	All lines			*Assembly lines*		
	(1)	(2)	(3)	(4)	(5)	(6)
Network strength (β)	0.113**	0.121***	0.158***	0.067*	0.110***	0.159***
	(0.045)	(0.028)	(0.042)	(0.037)	(0.034)	(0.038)
Constant	0.214*	0.232**	0.163*	0.402***	0.309***	0.328***
	(0.123)	(0.103)	(0.085)	(0.074)	(0.081)	(0.077)
Floor fixed effects	No	Yes	No	No	Yes	No
Line fixed effects	No	No	Yes	No	No	Yes
Number of observations	1043	1043	1043	868	868	868
Number of lines	37	37	37	31	31	31
R-square	0.484	0.588	0.700	0.537	0.641	0.697

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. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 2.5: Average line performance and composition

	Average efficiency of line					
	All lines			Assembly lines		
	(1)	(2)	(3)	(4)	(5)	(6)
Network strength (β)	0.247***	0.220***	0.235**	0.221**	0.241***	0.359**
	(0.075)	(0.065)	(0.111)	(0.090)	(0.085)	(0.137)
Constant	0.398**	0.461**	0.457*	0.311	0.395*	0.853**
	(0.196)	(0.171)	(0.246)	(0.215)	(0.222)	(0.396)
Floor fixed effects	No	Yes	No	No	Yes	No
Line fixed effects	No	No	Yes	No	No	Yes
Number of observations	1043	1043	1043	868	868	868
Number of lines	37	37	37	31	31	31
R-square	0.214	0.296	0.449	0.179	0.213	0.395

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. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 2.6: Worker performance and line composition (inverse probability weights)

	Worker efficiency					
	(1)	(2)	(3)	(4)	(5)	(6)
Network strength (β)	0.103**	0.103**	0.095**	0.103**	0.102**	0.094**
	(0.047)	(0.046)	(0.046)	(0.047)	(0.046)	(0.046)
Constant	0.276***	0.259***	0.328***	0.276***	0.258***	0.329***
	(0.019)	(0.075)	(0.071)	(0.019)	(0.075)	(0.071)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Floor fixed effects	No	Yes	No	No	Yes	No
Line fixed effects	No	No	Yes	No	No	Yes
Number of observations	34,641	34,641	34,641	34,623	34,623	34,623
Number of workers	1744	1744	1744	1740	1740	1740
Number of lines	37	37	37	37	37	37
R-square	0.550	0.550	0.555	0.549	0.550	0.554

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 1-3. Regressions weighted by inverse of the probability of worker being present on a workday in columns 4-6. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 2.7: Worker, line performance and composition (bootstrap standard errors)

	Worker efficiency		*Line level*			
			Minimum efficiency		*Average efficiency*	
	(1)	(2)	(3)	(4)	(5)	(6)
Network strength (β)	0.103**	0.095**	0.158***	0.158**	0.235*	0.235*
	(0.036)	(0.019)	(0.004)	(0.015)	(0.084)	(0.088)
Constant	0.276***	0.328**	0.064	0.163	0.511*	0.456*
	(0.000)	(0.012)	(0.564)	(0.126)	(0.086)	(0.08)
Individual fixed effects	Yes	Yes				
Line fixed effects	No	Yes	Yes	Yes	Yes	Yes
Number of observations	34,641	34,641	1043	1043	1043	1043
Number of workers	1744	1744				
Number of lines	37	37	37	37	37	37
R-square	0.550	0.013	0.273	0.700	0.001	0.449

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 1-2, 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 3-6. Regressions results with pairwise bootstrapped standard errors clustered at line level in columns 1, 3 and 5; pairwise bootstrapped standard errors in column 2; wild-cluster (at line level) bootstrapped standard errors in columns 4 and 6. 2000 replications across all regressions. Significant at *10%, **5% and ***1%.

Table 2.8: Job networks, residential location and caste

Panel A: Job informant characteristic	**No. 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 (in line on workday)	**No. of worker-days**	**Correlation**
Prop. residing in same cluster and prop. own caste	33862	0.033***
Prop. residing in same colony and prop. own caste	25313	0.032***
Prop. residing in same lane and prop. own caste	16838	0.097***

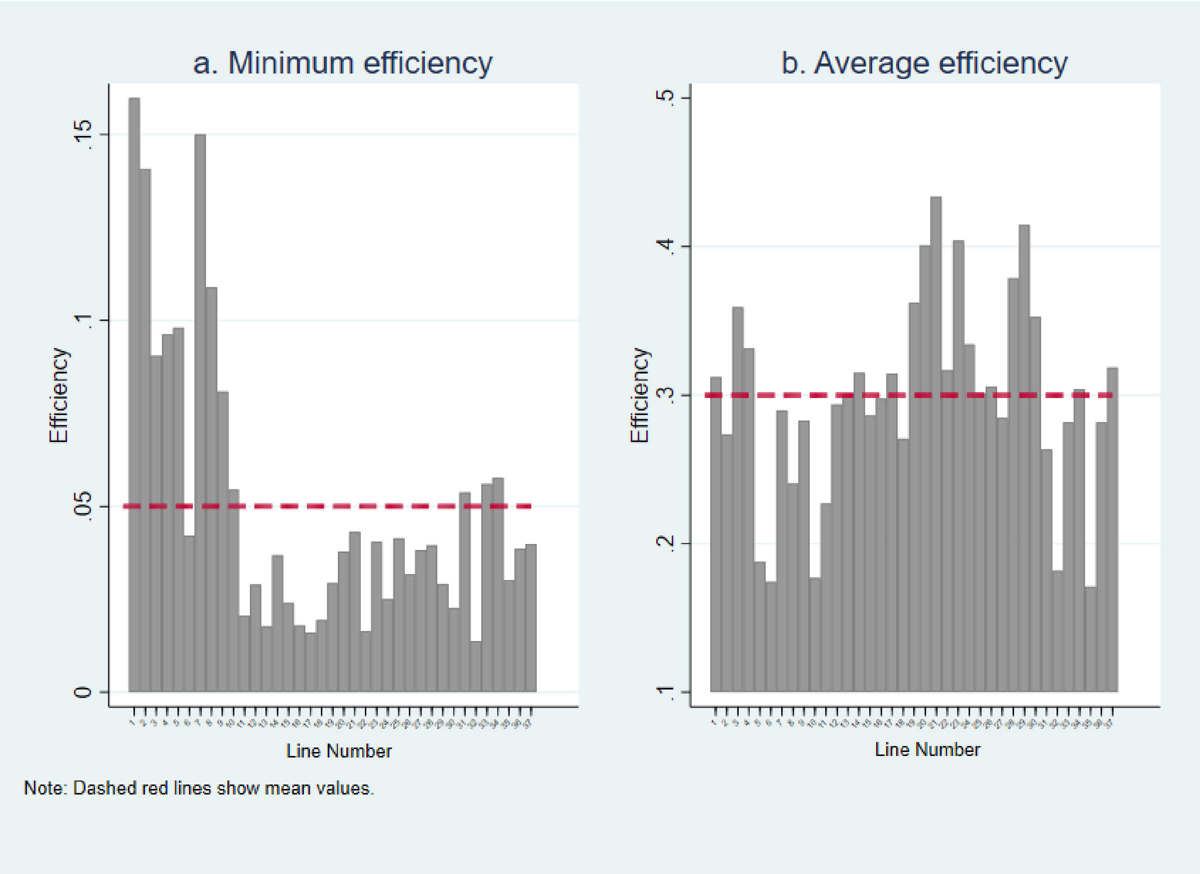
Note: @conditional on informal flow of job opening information; #smaller number of observation due non-response. In Panels B and C the sample is in worker-days, conditional on data on both caste and unit of residential location being available for a worker. Significant at *10%,**5% and ***1%.

Table 2.9: Worker, line performance and job referee presence

	Worker efficiency		Line Efficiency	
	(1)	(2)	(3)	(4)
(1) Proportion own caste	0.044	0.038		
	(0.047)	(0.046)		
(2) Proportion own caste x referee employed in factory	0.227***	0.225***		
	(0.062)	(0.059)		
(3) Caste concentration index			0.137	0.117*
			(0.146)	(0.064)
(4) Proportion with referee employed in factory			-0.107	-0.050
			(0.204)	(0.063)
(5) Caste concentration index x proportion with referee employed in factory			0.449	0.185
			(0.354)	(0.133)
Constant	0.266***	0.334***	0.609*	0.225***
	(0.075)	(0.071)	(0.301)	(0.069)
Effect of referee employed in factory: (4) + (5)			0.343*	0.135
			(0.189)	(0.087)
Individual fixed effects	Yes	Yes	No	No
Floor fixed effects	Yes	No	No	No
Line fixed effects	No	Yes	Yes	Yes
Number of observations	34,641	34,641	1043	1043
Number of workers	1744	1744		
Number of lines	37	37	37	37
R-square	0.551	0.555	0.454	0.704

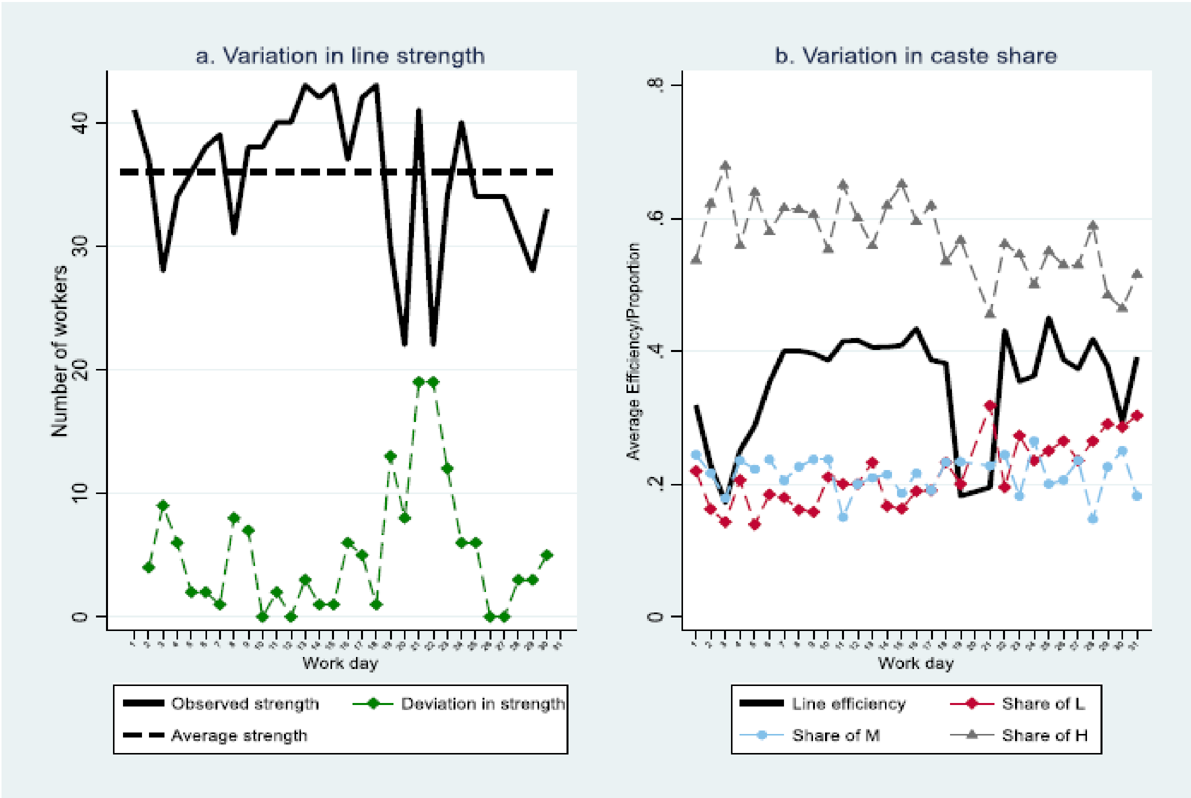
Note: In columns 1 and 2 the dependent variable is the efficiency of the worker on a work day. In column 3 the dependent variable in the average efficiency of the line. In column 4 the dependent variable is the minimum efficiency of the line. Referee employed in the factory is a dummy variable that takes 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). Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Figure 2.1: 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 2.2: Line performance and caste composition(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 2.3: 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=Σc_i^2, 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.

2.10 Appendices

2.A Additional Results

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

Line Number / Caste Category	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
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 Pearson's χ^2. Pearson's χ^2 statistics is 53.975 with 50 degrees of freedom and p value =0.325. We can't 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 2A.3: Chi-square test of exogeneity of caste assignment to line (domestic factory)

Line Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Caste Category											
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 Pearson's χ^2. Pearson's χ^2 statistics is 22.13 with 18 degrees of freedom and p value =0.226. We can't 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 2A.4: Worker attendance

	Attendance rate		Working days	
characteristics	(1)	(2)	(3)	(4)
Age (years)	0.001***	0.001***	0.051	0.060*
	(0.000)	(0.000)	(0.036)	(0.035)
Married	-0.013*	-0.013*	-1.798***	-1.583***
	(0.006)	(0.007)	(0.527)	(0.512)
Female	-0.010	-0.006	1.463**	1.757***
	(0.008)	(0.008)	(0.548)	(0.556)
Native state Bihar	0.014***	0.010**	0.636*	0.509*
	(0.004)	(0.005)	(0.352)	(0.298)
Hindu	0.032***	0.033***	2.534***	2.155***
	(0.010)	(0.010)	(0.632)	(0.609)
Secondary education or more	0.005	0.003	0.014	0.203
	(0.005)	(0.005)	(0.477)	(0.410)
Obtained job information informally	0.00004	0.0002	0.380	0.899*
	(0.005)	(0.006)	(0.570)	(0.460)
Experience (years)	-0.001***	-0.001***	0.322***	0.238***
	(0.0004)	(0.0005)	(0.062)	(0.055)
H	0.001	0.003	-0.356	-0.440
	(0.006)	(0.006)	(0.430)	(0.283)
M	0.008	0.006	0.280	0.064
	(0.007)	(0.007)	(0.503)	(0.453)
Number of reported friends	-0.0002	0.0004	0.089	0.227*
	(0.002)	(0.002)	(0.169)	(0.125)
Line supervisor same caste	-0.001	0.003	0.316	0.293
	(0.006)	(0.005)	(0.291)	(0.297)
Constant	0.865***	0.876***	14.36***	13.17***
	(0.014)	(0.013)	(1.204)	(0.869)
Line Fixed Effects	No	Yes	No	Yes
Number of workers	1731	1731	1735	1735
Psuedo-R2	0.023	0.052	0.041	0.197

Note: The first column uses factory attendance data. Attendance rate is the number of present days/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. The second column is based on the production data. Working days is the count of days a worker appears in the productivity data (excluding half days, 0.30% of the worker days). Robust standard errors, clustered at the line level, in parentheses. Attendance data missing for 4 workers; line information missing for 9 workers. Significant at *10%, **5% and ***1%.

Table 2A.5: Worker, line performance and caste composition

			Line level			
	Worker efficiency		Minimum efficiency		Average efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion own caste	0.079*	0.087**				
	(0.041)	(0.039)				
Caste concentration index			0.108***	0.139**	0.165**	0.172
			(0.031)	(0.046)	(0.067)	(0.112)
Constant	0.262***	0.240***	0.209**	0.111	0.366**	0.367
	(0.076)	(0.076)	(0.102)	(0.077)	(0.176)	(0.227)
Individual FE	Yes	Yes				
Floor FE	No	No	Yes	No	Yes	No
Line FE	Yes	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Line FE	No	Yes	No	Yes	No	Yes
Number of observations	34641	34641	1043	1043	1043	1043
Number of workers	1744	1744				
Number of lines	37	37	37	37	37	37
Psuedo-R2	0.565	0.576	0.607	0.752	0.362	0.586

Note: The dependent variable is worker efficiency in columns 1-2; minimum efficiency of line in columns 3-4 and average efficiency of line in columns 5-6. 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. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 2A.6: Worker performance and attendance rate

	Worker level			
	(1)	(2)	(3)	(4)
Proportion own caste	0.098	0.049	0.048	0.038
	(0.059)	(0.059)	(0.057)	(0.055)
Proportion own caste x Above median attendance	-0.046	0.086	0.087	0.089
	(0.066)	(0.069)	(0.068)	(0.070)
Constant	0.228***	0.275***	0.260***	0.332***
	(0.036)	(0.019)	(0.074)	(0.070)
Individual fixed effects	No	Yes	Yes	Yes
Floor fixed effects	No	No	Yes	No
Line fixed effects	No	No	No	Yes
Number of observations	34641	34641	34641	34641
Number of workers	1744	1744	1744	1744
Number of lines	37	37	37	37
R-square	0.013	0.550	0.550	0.555

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 worker attendance $\geq$ median work days; 0 otherwise. Median working days = 22. Robust standard errors, clustered at the line level, in parentheses. Significant at *10%,**5% and ***1%.

Table 2A.7: Dispersion in worker performance and network strength

	Dispersion in worker productivity			
	(1)	(2)	(3)	(4)
Caste concentration index	0.093*	0.080**	0.066	0.051
	(0.055)	(0.031)	(0.064)	(0.060)
Constant	0.165	0.238**	0.176	0.156
	(0.159)	(0.110)	(0.153)	(0.156)
Floor fixed effects	No	Yes	No	No
Line fixed effects	No	No	Yes	Yes
Months fixed effects	No	No	No	Yes
Number of observations	1041	1041	1041	1041
Number of lines	37	37	37	37
R-square	0.314	0.512	0.584	0.586

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. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Table 2A.8: Worker performance, experience and network strength

	Minimum efficiency			
	(1)	(2)	(3)	(4)
Caste concentration index (CCI)	-0.159*	-0.120	-0.028	-0.078
	(0.091)	(0.086)	(0.087)	(0.082)
Proportion high experience	-0.326***	-0.250***	-0.170***	-0.175***
	(0.076)	(0.075)	(0.054)	(0.048)
Proportion high experience x CCI	0.598***	0.538***	0.398**	0.445***
	(0.173)	(0.174)	(0.149)	(0.147)
Constant	0.360***	0.304***	0.266***	0.244***
	(0.094)	(0.073)	(0.081)	(0.075)
Floor fixed effects	No	Yes	No	No
Line fixed effects	No	No	Yes	Yes
Months fixed effects	No	No	No	Yes
Number of observations	1043	1043	1043	1043
Number of lines	37	37	37	37
R-square	0.537	0.616	0.709	0.728

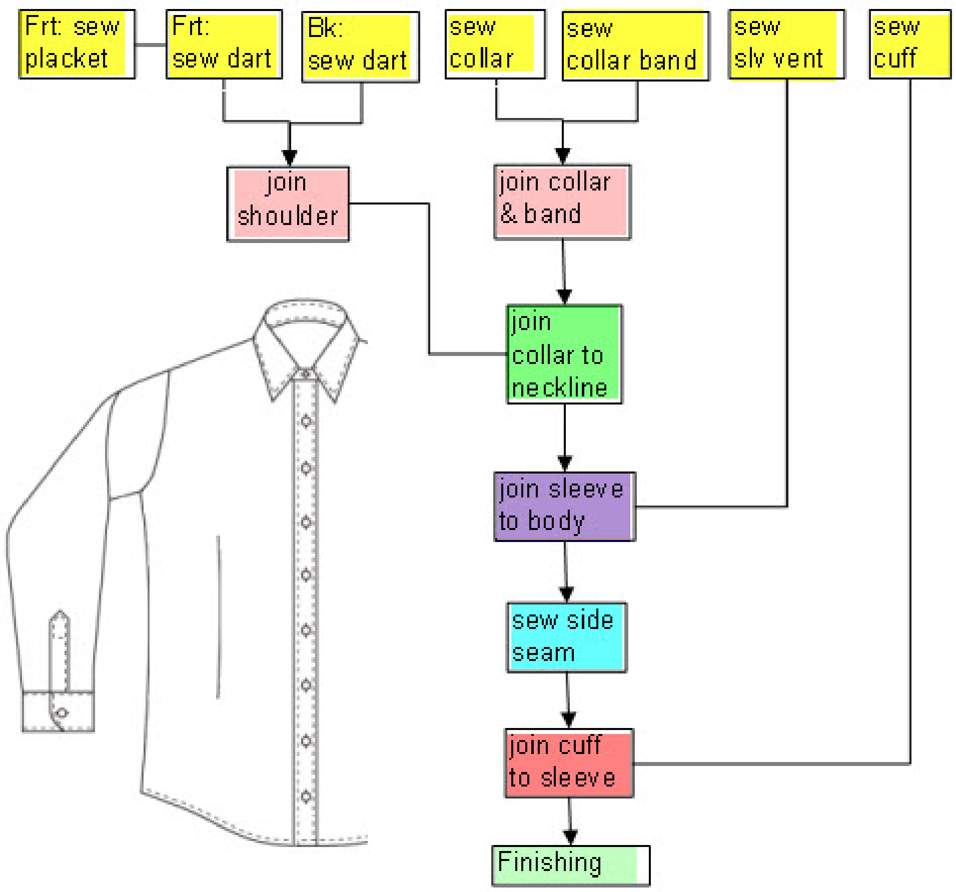
Note: The dependent variable is the minimum efficiency of workers in a line on a work day. 'Proportion high experience' is the number of workers with above or equal to median years of experience in the garment industry sitting in line l on day d /strength in line l on day d. Median experience in garment 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. Robust standard errors, clustered at line level, reported in parentheses. Significant at *10%, **5% and ***1%.

Figure 2A.1: Factory floor and line organisation

Location: Faridabad

Source: icrw.org

Figure 2A.2: Manufacturing process of a shirt



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

2.B Theoretical Framework

Benchmark model without social networks

The optimization problem is to choose w_1, w_2 to maximize (per worker expected profit):

$$E(\pi(e_h, e_h)) = \theta + \pi_{h,h} - \alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2 \tag{2B.1.1}$$

subject to the incentive compatibility (IC) constraints, the participation constraints (PC) and a limited liability (LL) constraint. (1) the PC says that a worker will only accept the implicit contract offering expected wages $\alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2$ if the cost of effort is low enough that utility is higher than the outside option of minimum wages in another firm:

$$\alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2 - c \geq \underline{w} \tag{2B.1.2}$$

which can be re-written as

$$\alpha^{hh} (w_1 - w_2) + w_2 - c \geq \underline{w} \tag{2B.1.3}$$

(2) The ICs: 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 that high effort is a dominant strategy for worker i: IC(1)(worker j puts in high effort)

$$\alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2 - c \geq \alpha^{lh} w_1 + (1 - \alpha^{lh}) w_2 \tag{2B.1.4}$$

which can be re-written as:

$$(\alpha^{hh} - \alpha^{lh})(w_1 - w_2) \geq c \tag{2B.1.5}$$

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

$$\alpha^{hl} w_1 + (1 - \alpha^{hl}) w_2 - c \geq \alpha^{ll} w_1 + (1 - \alpha^{ll}) w_2 \tag{2B.1.6}$$

which can be re-written as:

$$(\alpha^{hl} - \alpha^{ll})(w_1 - w_2) \geq c \tag{2B.1.7}$$

and (3) the LL constraint: $w_1, w_2, w_3 \geq \underline{w}$

Lemma 2.B.1. *The solution to the maximization problem (2B.1.1) is* $w_1 = \underline{w} + \frac{c}{\alpha^{hl}-\alpha^{ll}}$ *and* $w_2 = \underline{w}$.

Proof. Since $(\alpha^{hh} - \alpha^{lh}) > (\alpha^{hl} - \alpha^{ll})$, IC (2B.1.7) $\implies$ IC(2B.1.5). Moreover IC (2B.1.7) $\implies$ $w_1 > w_2$. Let $w_2 = w$ be the base wage and $w_1 - w_2 = b$, the bonus. Then we have the following solution $w_1 = w + b = \underline{w} + \frac{c}{\alpha^{hl}-\alpha^{ll}}$ and $w_2 = \underline{w}$. This solution satisfies the PC. □

Expected profits, assuming all workers get the same wages are: $E(\pi(e_h, e_h)) = \underline{\theta} + \bar{\theta} + 2(\pi_{h,h} - \alpha^{hh}(\underline{w} + \frac{c}{\alpha^{hl}-\alpha^{ll}}) + (1 - \alpha^{hh})\underline{w})$. Denote average ability as $\mu = \frac{\underline{\theta}+\bar{\theta}}{2}$. Then expected profits per worker are: $E(\pi(e_h, e_h)) = \mu + \pi_{h,h} - \alpha^{hh}(\underline{w} + \frac{c}{\alpha^{hl}-\alpha^{ll}} - (1 - \alpha^{hh})\underline{w}$.

Alternately, the firm can induce high effort only from one worker. Since ability is observable, w.l.o.g the firm would find it profitable to pay higher wages to induce high effort from the high ability worker and induce low effort (and pay minimum wages) from the low ability worker (or vice versa as long as only one worker is induced to put in high effort). Then the problem for the high ability worker is to choose w_1, w_2 to maximize:

$$E(\pi(e_h, e_l)) = \bar{\theta} + \pi_{h,l} - \alpha^{hl} w_1 + (1 - \alpha^{hl}) w_2 \tag{2B.1.8}$$

subject to:

(1) the PC:

$$\alpha^{hl} w_1 + (1 - \alpha^{hl}) w_2 - c \geq \underline{w} \tag{2B.1.9}$$

which can be re-written as:

$$\alpha^{hl}(w_1 - w_2) + w_2 - c \geq \underline{w} \tag{2B.1.10}$$

(2) The IC

$$\alpha^{hl} w_1 + (1-\alpha^{hl}) w_2 - c \geq \alpha^{ll} w_1 + (1-\alpha^{ll}) w_2 \tag{2B.1.11}$$

which can be re-written as:

$$(\alpha^{hl} - \alpha^{ll})(w_1 - w_2) \geq c \tag{2B.1.12}$$

and (3) the LL constraint: $w_1, w_2, w_3 \geq \underline{w}$

Lemma 2.B.2. *The solution to the maximization problem (2B.1.8) is* $w_2 = \underline{w}, w_1 = \underline{w} + \frac{c}{(\alpha^{hl}-\alpha^{ll})}$.

The proof follows the same logic as the proof of Lemma (2.B.1). By the same logic, $w_2 = \underline{w}, w_1 = \underline{w} + \frac{c}{(\alpha^{hl}-\alpha^{ll})}$. Total costs are now $\alpha^{hl}\frac{c}{(\alpha^{hl}-\alpha^{ll})} + \underline{w}$ and expected profits are positive iff $\mu + \pi_{h,l} - \alpha^{hl}(\frac{c}{\alpha^{hl}-\alpha^{ll}}) - \underline{w} \geq 0$.

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 $\mu + \pi_{ll} - \underline{w} \geq 0$.

What effort profile will the firm induce? Observe that (1) Expected profits with high effort for both workers are higher than expected profits when only one worker is induced to put in high effort if $\bar{\theta} + \underline{\theta} + 2\pi_{h,h} - 2\alpha^{hh}(\frac{c}{\alpha^{hl}-\alpha^{ll}}) - 2\underline{w} \geq \bar{\theta} + \underline{\theta} + 2\pi_{h,l} - \alpha^{hl}(\frac{c}{\alpha^{hl}-\alpha^{ll}}) - 2\underline{w}$, i.e. iff $\pi_{h,h} - \pi_{h,l} \geq (\alpha^{hh} - \frac{\alpha^{hl}}{2})(\frac{c}{\alpha^{hl}-\alpha^{ll}})$. (2) Expected profits with high effort for both workers are higher than expected profits when no worker is induced to put in high effort iff $\mu + \pi_{h,h} - \alpha^{hh}(\frac{c}{\alpha^{hl}-\alpha^{ll}}) - \underline{w} \geq \mu + \pi_{ll} - \underline{w}$. Thus high effort is induced for both workers when both (1) and (2) hold, or

$$x_1 - x_2 \geq \frac{2\alpha^{hh} - \alpha^{hl}}{2(\alpha^{hh} - \alpha^{hl})} \frac{c}{\alpha^{hl} - \alpha^{ll}} \tag{2B.1.13}$$

and

$$x_1 - x_2 \geq \frac{\alpha^{hh}}{\alpha^{hh} - \alpha^{ll}} \frac{c}{\alpha^{hl} - \alpha^{ll}} \tag{2B.1.14}$$

Let $T_1 \equiv \frac{2\alpha^{hh}-\alpha^{hl}}{2(\alpha^{hh}-\alpha^{hl})}\frac{c}{\alpha^{hl}-\alpha^{ll}}$ and $T_2 \equiv \frac{\alpha^{hh}}{\alpha^{hh}-\alpha^{ll}}\frac{c}{\alpha^{hl}-\alpha^{ll}}$. The firm induces high effort from both workers iff $x_1 - x_2 \geq max(T_1, T_2)$.

Inequality (2B.1.13) $\implies$ inequality (2B.1.14) iff $\frac{2\alpha^{hh} - \alpha^{hl}}{2(\alpha^{hh} - \alpha^{hl})} \geq \frac{\alpha^{hh}}{\alpha^{hh} - \alpha^{ll}}$. A necessary and sufficient condition for this is that the degree of complementarity is sufficiently high, i.e $\alpha^{hh} - \alpha^{ll} > A(\alpha^{hh} - \alpha^{hl})$, where $A = \frac{2\alpha^{hh} - \alpha^{hl}}{2\alpha^{hh}}$. This leads to our first Proposition (1):

Proposition 1. *Assume that the firm makes positive profits when low effort is induced for both workers, i.e.* $\mu \geq \underline{w} - \pi_{l,l}$. *The firm induces high effort in both workers iff* $x_1 - x_2 \geq \max(T_1, T_2)$. *Expected wages are* $\alpha^{hh} \frac{c}{(\alpha^{hl} - \alpha^{ll})} + \underline{w}$ *for each worker. If* $T_1 > T_2$, *(the degree of complementarity in the production function is sufficiently high) and* $x_1 - x_2 < T_1$, *then the firm induces high effort in the high ability worker and low effort in the low ability worker. The corresponding expected wages are* $\alpha^{hl} \frac{c}{(\alpha^{hl} - \alpha^{ll})} + \underline{w}$ *to the high ability worker and* $\underline{w}$ *to the low ability worker. If* $T_2 > T_1$ *and* $x_1 - x_2 < T_2$ *then the firm induces low effort in both types of workers. The corresponding wages are* $\underline{w}$ *for each worker.*

The proof is obvious.

With social networks

Recall the utility function, (2.6), with social networks. $V(f_i^k|e)$ depends only on the effort level of worker i and $V(f_i^k|e_l) = \underline{V} < V(f_i^k|e_h)$. Suppose the firm wants to induce high effort in both workers. Re-writing (2.2):

(1) the PCs:

$$\gamma(E(w|e_h, e_h) - c) + (1-\gamma)V(f_i^k|e_h) \geq \gamma\underline{w} + (1-\gamma)\underline{V} \tag{2B.2.1}$$

which can be re-written as:

$$\alpha^{hh} w_1 + (1 - \alpha^{hh}) w_2 \geq c + \underline{w} - \frac{(1-\gamma)}{\gamma}(V(f_i^k|e_h) - \underline{V}) \tag{2B.2.2}$$

(2) The ICs

$$\gamma(\alpha^{hh} w_1 + (1-\alpha^{hh}) w_2 - c) + (1-\gamma)V(f_i^k|e_h) \geq \gamma(\alpha^{lh} w_1 + (1-\alpha^{lh}) w_2) + (1-\gamma)\underline{V} \tag{2B.2.3}$$

which can be re-written as:

$$(\alpha^{hh} - \alpha^{lh})(w_1 - w_2) \geq c - \frac{1-\gamma}{\gamma}(V(f_i^k|e_h) - \underline{V}) \tag{2B.2.4}$$

and

$$\gamma(\alpha^{hl} w_1 + (1-\alpha^{hl})w_2 - c) + (1-\gamma)V(f_i^k|e_h) \geq \gamma(\alpha^{ll} w_1 + (1-\alpha^{ll})w_2) + (1-\gamma)\underline{V} \tag{2B.2.5}$$

which can be re-written as:

$$(\alpha^{hl} - \alpha^{ll})(w_1 - w_2) \geq c - \frac{1-\gamma}{\gamma}(V(f_i^k|e_h) - \underline{V}) \tag{2B.2.6}$$

and (3) the LL constraint: $w_1, w_2, w_3 \geq \underline{w}$

Denote $\frac{1-\gamma}{\gamma}(V(f_i^k|e_h) - \underline{V}) = K$. Then the inequalities (2B.2.1) to (2B.2.6) are the same as inequalities (2B.1.2) to (2B.1.7) except for the RHS which is now lower at $c-K$. Suppose the firm wants to induce low effort by both workers. There are no incentive constraints. Since $V(f_i^k|e_l) = \underline{V}$ the wages that satisfy the participation constraint are $w_1 = w_2 = \underline{w}$. Below we assume $c > K$ to ensure that the bonus for high effort is positive.

Let $\tilde{T}_1 \equiv \frac{2\alpha^{hh}-\alpha^{hl}}{2(\alpha^{hh}-\alpha^{hl})}\frac{c-K}{\alpha^{hl}-\alpha^{ll}}$ and $\tilde{T}_2 \equiv \frac{\alpha^{hh}}{\alpha^{hh}-\alpha^{ll}}\frac{c-K}{\alpha^{hl}-\alpha^{ll}}$. This proves Proposition (2), below:

Proposition 2. *Assume that the firm makes positive profits when low effort is induced for both workers, i.e.* $\mu \geq \underline{w} - \pi_{l,l}$ *and* $c > K$. *The firm induces high effort in both workers iff* $x_1 - x_2 \geq \max(\tilde{T}_1, \tilde{T}_2)$. *Expected wages are* $\alpha^{hh}\frac{c-K}{(\alpha^{hl}-\alpha^{ll})} + \underline{w}$ *for each worker. If* $\tilde{T}_1 > \tilde{T}_2$, *(the degree of complementarity in the production function is sufficiently high) and* $x_1 - x_2 < \tilde{T}_1$, *then the firm induces high effort in the high ability worker and low effort in the low ability worker. The corresponding expected wages are* $\alpha^{hl}\frac{c-K}{(\alpha^{hl}-\alpha^{ll})} + \underline{w}$ *to the high ability worker and* $\underline{w}$ *to the low ability worker. If* $T_2 > T_1$ *and* $x_1 - x_2 < T_2$ *then the firm induces low effort in both types of workers. The corresponding wages are* $\underline{w}$ *for each worker.*

Chapter 3

Using Social Connections and Financial Incentives to Solve Coordination Failure: A Quasi-Field Experiment in India's Manufacturing Sector[1]

3.1 Introduction

It is well acknowledged that labor productivity in developing countries is low compared to the developed world (Bloom et al. (2013)). Recent literature has looked inside the black-box of the factory to understand the determinants of worker performance, including the important roles of social networks (Bandiera et al. (2009)), management practices (Bloom et al. (2013)), and worker ethnicity (Hjort (2014)). Indeed, productivity data from Chapter 2 shows significant variation in the productivity of teams within the same factory and its correlation with changes in team composition. This chapter investigates whether exogenous changes in social connections between work-

[1]This paper is a joint work with Farzana Afridi (ISI-Delhi), Amrita Dhillon (King's College London), Sherry Xin Li (University of Arkansas), and is published. Refer to Afridi et al. (2020a).

ers in a team, pre-determined by caste and residential segregation, affect individual and group performance in a coordination task using a lab-in-the-field experiment in India's garment manufacturing sector.[2] Unlike the existing literature, this chapter also focuses on production processes characterized by complementarities between workers, as in assembly lines in manufacturing units. We not only highlight the potentially positive role of social connections in tasks requiring coordination, but also throw light on the role of financial incentives in improving group productivity and coordination.

Our experiment randomly assigns subjects to teams with or without pre-existing social ties in an incentivized coordination task which replicates assembly line production using garment factory workers as subjects. We make social ties salient through a one shot announcement of the group composition which contains information on workers' caste and residential address. Our experiment is, thus, designed to focus on how the pre-existing connections of co-workers belonging to the same social networks affect coordination and productivity. Furthermore, we examine the role of financial incentives as an instrument for overcoming coordination failure (Brandts and Cooper (2006), Brandts and Cooper (2007)) by introducing a lump sum bonus, if a threshold level of group output is produced, that incentivizes a feasible focal point for the workers.

Motivated by the large assembly lines in garment factories in India, where team composition changes frequently due to high worker absenteeism, turnover (Ministry of Textiles, GOI (2018)) and limited scope for communication or repeat interactions among co-workers, we shut down the observability of effort and communication among workers. We, therefore, abstract from peer effects which have been shown to lead to conformism in worker productivity (e.g. Mas and Moretti (2009), Bandiera et al. (2009)). Our experimental design allows us to measure individual and group output simultaneously, giving us a precise measure of coordination or wasted effort within groups directly as a result of our treatments.

[2]This is built on the evidence from Chapter 2 that workers reside in residential neighborhoods that are highly segregated by caste. Same caste workers are, therefore, more likely to belong to the same social networks.

In the context of developing countries, where social networks are very strong, the question of how social connections affect productivity is key to the development process (Munshi (2014)). Social ties among co-workers are particularly relevant when workers are organized in groups, such as assembly lines, and when firms are concerned with group rather than individual outputs. In such a setting, if some workers put in low effort it can lead to the entire team being trapped in a low effort equilibrium. Munshi (2014) notes that members of social networks may respond to the threat of social sanctions by sacrificing individual gain (i.e., by incurring higher effort cost) in favor of group objectives. On the other hand, individuals may feel altruistic towards group members or trust co-workers with whom they are socially connected (Basu (2010)), resulting in greater cooperative behavior when they are matched with workers who are in the same social network.

3.1.1 Main results

In our setting of a minimum effort production function, subjects respond positively to being with co-workers with whom they have social connections – being in a socially connected group leads to 18% higher *group* output, although *individual* output increases insignificantly relative to the unconnected. Furthermore, there is a 30-39% decline in wasted individual output and within-group output dispersion vis-a-vis an unconnected group. Our findings, therefore, suggest that stronger social connections among co-workers can enhance coordination when incentives are group based. Since we eliminated peer effects and did not allow for any communication within group members in our experiment design, the estimates we obtain here might be a lower bound for the impact of social connections on individual and group productivity in our context (for instance, Menzel (2018) who does allow communication, shows an increase in the assembly-line production in garment factories in Bangladesh).

The impact of our bonus incentive is statistically insignificant overall, suggesting that higher financial incentives neither increase (individual or group) output nor improve within-group coordination, irrespective of social connectedness of the groups.

This may not be surprising given the findings of Brandts and Cooper (2006) who show that financial incentives work only to improve coordination if they are large enough, or if agents are allowed to learn over time. Our real-effort minimum-effort game is one shot, which may explain the lack of immediate impact of stronger financial incentives on output and coordination of the group. However, we find that high powered monetary incentives may help increase individual effort of groups which produce below the bonus threshold, irrespective of within-group connectedness.

We show theoretically that our results can plausibly be explained by pro-social behavior driven by network contingent social preferences (Basu (2010), Chen and Li (2009), Chen and Chen (2011)) in socially connected teams.[3] When peer effects and communication channels are absent we argue that the mechanism underlying our results is beliefs about co-workers' effort levels. When ability levels are heterogeneous the lowest ability worker, who constrains the maximum output of a group, is willing to put in higher effort in the connected group because he internalises the lower cost of other higher ability workers. Thus the *group* output increases due to the higher effort of the lowest ability worker in the socially connected group. Hence *individual* effort, on average, may not be higher in the connected than unconnected groups, but group coordination and output are.

3.1.2 Related literature

A closely related literature has examined the role of social networks on worker productivity. Bandiera et al. (2010) study a UK based soft fruit producing firm and find that having a more able, self-reported friend as a co-worker increases productivity of lower ability workers by 10% but decreases productivity of higher ability workers. Overall, in the presence of individual piece rates, heterogeneous ability types, and substitutability in production, their findings indicate that social networks may not improve team productivity if peer pressures lead to conformity on a low effort norm.

[3]Note that defining social connections based on caste, which is determined at birth, allows us to circumvent any selection issues. For example, social connections that arise endogenously may result in connected groups that are sorted on ability or preferences.

Our research question, in contrast, is centred on understanding whether coordination can improve in assembly lines when workers belong to the same social networks. Thus we focus on the effect of social networks in the absence of peer effects with complementarity in production and team based incentives.

Laboratory experiments on group identity, in general, show that manipulating the saliency of group membership contributes to higher level of within-group cooperation or coordination (Eckel and Grossman (2005), Charness et al. (2007), Goette et al. (2006), Chen and Li (2009), Chen and Chen (2011)). In a rare field experiment on group identity, Hjort (2014), examines the ethnic homogeneity of production teams in a flower assembly plant with a sequential production process in Kenya. He finds that inter-ethnic rivalries in Kenya lowers allocative efficiency in the plant, particularly during a period of ethnic conflict. Shifting from fixed pay to performance pay based on group output reduces allocative inefficiencies in multi-ethnic teams. Unlike this literature, however, our paper does not prime group identity but rather the social connections among team members. Theoretically, our approach yields similar predictions as Chen and Chen (2011), but to the best of our knowledge, this is the first paper to conduct a lab-in-the field experiment with a real-effort task on the minimum effort game.

Our study, thus, attempts to bridge the disconnect between field experiments on social networks and labor productivity, which have focused on non-complementary production functions, and the large literature on laboratory experiments on coordination games.[4] Unlike Bandiera et al. (2009, 2010) who study team incentives when workers are substitutes in production or Hjort (2014) who examines team incentives in settings where production is sequential and there is both substitutability and complementarity in production, our study design is suited to contexts where workers si-

[4]Minimum-effort (or weak-link) coordination game with multiple Pareto-ranked equilibrium effort levels was first introduced by (Van Huyck et al. (1990)), and has been widely used in the laboratory to understand coordination problems faced by organizations (Brandts and Cooper (2006), Weber (2006)). In addition, much of the experimental literature has focused on how to improve coordination and efficiency by altering the payoff structure of the game (Brandts and Cooper (2007), Goeree and Holt (2003), Devetag and Ortmann (2007), Van Huyck et al. (2007)), or by introducing communication (Blume and Ortmann (2007), Brandts et al. (2007), Kriss et al. (2016)) or group identity salience (Chen and Chen (2011)).

multaneously engage in a production task and may not be able to observe each other's effort or communicate to coordinate on output.

The findings of our paper not only extend the literature on worker incentives but also speak to the existing research on management practices and firm behavior. First, our results suggest that management practices that create avenues for co-worker interactions to foster affinity among them can further enhance group productivity if individual payoffs are contingent on group output. Second, Brandts and Cooper (2006) show that increasing marginal rewards to effort acts as a coordinating device to move to the efficient equilibrium. Our attempt to replicate the bonus design from the factory settings, however, suggests that the bonus instead creates a focal point which may not always lead to higher group output, unless the threshold for the bonus is sufficiently high. Finally, our findings have implications both for large assembly lines with limited scope for communication and for emerging contemporary work practices such as O-Desk where work is performed in online teams and where face-to-face interactions and scope for communication is limited. In such settings, our results point to the increased productivity from team-based social incentives.

The remainder of the chapter is organized as follows. Section 3.2 outlines the context and background of the study while section 3.3 discusses the theoretical framework that we take to the data. We describe the experiment design in detail in section 3.4. The empirical methodology and results are discussed in section 3.5 while section 3.6 concludes.

3.2 Context and Background

Historical and economic factors suggest that formation of social networks based on caste and homophily is salient in the Indian context. Chandavarkar (1994) documents that historically migration to industrial hubs occurred within the framework of caste, kinship, and village connections in India.[5] Migrants to the city lived with their co-

[5] 30% of the Indian population has migrated from another part of the country at some point, of which almost 15% migrate for employment purposes (Census, GOI (2011)).

villagers, caste-fellows, and relatives and sought work with their assistance (Gokhale (1957), Cholia (1941), Burnett-Hurst (1925)). Thus caste and kinship formed indivisible social networks in the city's working-class neighborhoods. As industrialization progresses, social networks continue to play a significant role in the functioning of labor markets (Afridi et al. (2015a)) and in ensuring migrants' economic mobility in the modern age in low income countries (Munshi (2014), Beaman and Magruder (2012)). Migrants tend to find employment through referrals from their caste-based networks and hence often locate within the same residential units post migration. Given this sociological context, we focus on co-worker connections based on the caste system in India.[6]

We used the Indian garment manufacturing factories settings to show the impact of socio-economic interdependence within social networks on worker's performance in the previous chapter. This chapter also draws on labor-intensive garment manufacturing sector. As described in chapter 2, garment manufacturing is one of the most prominent employer in manufacturing and also a major contributor to exports not only in India but also in other developing countries such as Bangladesh, Pakistan, and China (Lopez-Acevedo and Robertson (2016)).[7] This sector thus provides a natural choice for advancing our understanding of worker performance in the Indian and other developing country context.

In this chapter, we highlight the role of pro-social motivations among socially connected workers as a salient feature that affects output and coordination within groups. We formally elaborate on the challenge of coordinating workers' effort in a minimum effort game in our theoretical model next.

[6]Introduced thousands of years ago, the caste system has continued to socially stratify Indians even today into four hierarchical categories (*varnas*), each of which is further sub-divided into *jatis* having a common origin in terms of occupation, language, and social practices. At the top of the social hierarchy are *Brahmins* (the priestly caste), followed by the *Kshatriyas* (the warrior caste), *Vaishyas* (the trading caste), and finally *Shudras* (the service caste such as farmers and craftsmen) in the *varna* system of social categorization. The caste system is endogamous, and hence one's caste is determined at birth. Inter-caste marriages are virtually non-existent even today (India Human Development Survey, 2014 (https://ihds.umd.edu/)).

[7]Garment manufacturing sector employed more than 45 million people in 2016-17 in India.(Ministry of Textiles, GOI (2018), (http://www.texmin.nic.in/study-garment-sector-understand-their-requirement-capacity-building)).

3.3 Theory

Motivated by the stylised facts in Section 3.2, we build on a version of the coordination problem in a minimum effort game (Van Huyck et al. (1990)), which captures the strong complementarities in an assembly line setting.[8] In the standard minimum effort game, workers are homogeneous and choose effort to maximize their own payoffs which depend on group production, which in turn depends only on the lowest effort (output) among workers. The game has multiple Nash equilibria which can be Pareto ranked. Thus groups that are able to coordinate on a higher ranked equilibrium perform better. In our modification, we introduce heterogeneous (ability) types, which is more realistic in our setting and also allows us to distinguish between group and individual effort, as well as conceptualise wasted effort in symmetric equilibria.

Formally, workers are characterised by – first, their ability type: high ability denoted by $\bar{\theta}$ and low ability denoted by $\underline{\theta} < \bar{\theta}$, and second, their social connectedness.[9] Workers may or may not be socially connected to co-workers depending on their caste, i.e. High (**H**), Middle (**M**) or Low (**L**) caste, and residential location – as in our experiment. We assume that there is perfect information on the game and that the distribution of ability is the same across caste groups (as confirmed by our data, see Table 3A.2, Appendix 3.A). In addition, workers are equally likely to be low ($\underline{\theta}$) or high ability ($\bar{\theta}$).

Workers are matched randomly on ability to form teams of size 2. Teams can be either socially connected, i.e. belong to the same social network (defined by same caste and residence), or unconnected (where caste types are mixed). Thus a high (low) ability worker is equally likely to be matched with a high or low ability worker, implying that the ability distribution is the same between connected and unconnected teams. The ability match between two workers in the (connected or unconnected) team is ei-

[8] We consider a one-shot game to account for the low scope for communication or repeat interactions among co-workers due to daily changes in group composition in garment factories.

[9] Formally, we do not need to assume heterogeneity in ability – workers can be heterogeneous in the degree of pro-social motivation as well. In this case, our key assumption would be that the distribution of social preferences for connected workers first order stochastically dominates the distribution for unconnected workers. The results would be qualitatively the same.

ther *homogeneous*, i.e. $\theta_i = \theta_j$, or *heterogeneous* i.e $\theta_i \neq \theta_j$.[10] Note that homogeneous teams can be either high ability or low ability. Workers choose effort $e_i \in \{\overline{e}, \underline{e}\}$, where $\bar{e} > \underline{e} > 0$. Each worker produces individual output $y_i = \theta_i e_i$. The production function is a minimum output one: group output is equal to the minimum production across workers in the team, $Y = min[\theta_i e_i, \theta_j e_j]$.

The salient characteristic of social networks that we focus on in the model is the degree of pro-social motivation towards other team members. This takes the form of maximizing a weighted sum of one's own payoff and the other player's payoffs, with weights α_i and $1 - \alpha_i$, respectively. It is formally the same as a group-contingent social preferences model that has been shown (theoretically) to increase cooperation/coordination in groups with salient group identity (see e.g. Basu (2010), Chen and Chen (2011), Chen and Li (2009)). Such pro-social motivation is present to a lesser degree in the socially unconnected groups.[11] α_i reflects the degree of selfishness of worker i. We will assume that $\alpha_i = \alpha_j$ for all members i, j in a group. Thus, denote by α^C (α^U), the weight on own payoffs for connected (unconnected) groups. We have $\alpha^C < \alpha^U$.[12] In effect this implies that the marginal cost of effort is lower for the connected group ($c\alpha^C < c\alpha^U$). We assume that the utility function for worker i is $U_i = \alpha_i(DY - ce_i) + (1 - \alpha_i)(DY - ce_j) = DY - c(\alpha_i e_i + (1 - \alpha_i)e_j)$.[13] $c > 0$ is a constant that affects the marginal cost of effort, and $D > 0$ measures the strength of financial incentives (group based piece rates).

In Table 3.1 we depict the game between workers who can either be socially connected or not, when the match is homogeneous, $\theta_i = \theta_j$.[14] In the standard minimum

[10]Of course, in reality there will never be cases where all workers have exactly the same ability but this is a stylised representation of two different cases: one where the difference in ability between workers is small and the other when it is relatively large.

[11]Laboratory experiments on coordination allow for repetitions of the game to check convergence to different equilibria. In contrast, we have a one shot announcement of group composition because our main interest is to understand how knowledge of group composition affects worker productivity and coordination. This is why much of the analysis is framed in terms of the probability of converging to a particular equilibrium.

[12]Note that modelling social preferences in an additive way is not necessary for the results – we only need that the cost of effort is lower when the partner is from the same network, see e.g. Bandiera et al. (2010) who also model social preferences in worker productivity in the same way.

[13]For n players the corresponding utility function is a convex combination of own payoff and the average payoff of other players.

[14]We use linear payoffs as this is a tractable way to show our results and this is the format that has

effort game, when $\alpha_i = 1$, it is well known that when $D\underline{\theta} - c > 0$, there are two symmetric pure strategy Nash equilibria: one where both players coordinate on the higher effort, another where they coordinate on the lower effort, as well as a mixed strategy equilibrium. This result carries over to our homogeneous game, even when $\alpha < 1$. Both pure strategy equilibria are stable. Which equilibrium is more likely to occur depends on the basin of attraction. Let p_j denote the probability on high effort by player j and $EU_i(e)$ denote the expected utility of player i when his effort level is e. Let $\underline{p} = \{\min p_j | EU_i(\bar{e}) > EU_i(\underline{e})\}$, where $\underline{p}$ denotes the minimum expected probability (belief) of the opponent playing high effort, which would lead to each player playing high effort.[15] $\underline{p}$ is increasing in the rewards to high effort – D and θ – and decreasing in c and α.

For our purposes, the key parameter is α which affects the beliefs about other workers choice of effort. Thus the lower is α, the lower is $\underline{p}$ and the higher the beliefs about others putting in high effort.[16] The lower is $\underline{p}$ the more likely it is that the high effort equilibrium is selected – this is because players believe that others are more likely to choose high effort, which in turn creates positive incentives to choose high effort themselves. Clearly, coordination on the high effort equilibrium is higher when $\underline{p} \to 0$, and coordination on the low effort equilibrium is higher when $\underline{p} \to 1$. We denote by $\underline{p}^U$ ($\underline{p}^C$) the minimum expected probability (belief) of the opponent playing high effort, in the unconnected (connected) game. We will say that coordination is higher for a selected equilibrium when the corresponding condition on $\underline{p}$ is satisfied. For example, if the selected equilibrium is the high effort equilibrium then coordination is higher on high effort for the connected group if and only if $\underline{p}^C < \underline{p}^U$.[17]

Next, we depict the game when the match between workers is heterogeneous

been used in the literature on minimum effort games.

[15]Note that by symmetry of the game, $\underline{p}$ is the same for both players if they are of the same type.

[16]Even if we assumed that a single player has pro-social preferences and this is common knowledge, we would still get a higher push towards the high effort equilibrium. To see this, note that in the limit as $\alpha_j \to 0$ it becomes a dominant strategy for the other player to choose $\bar{e}$ and given that, the optimal choice for own effort is also $\bar{e}$. Besides reducing own cost of effort, pro social motivation also reduces strategic uncertainty.

[17]If one group is more likely to choose high effort while the other is more likely to choose low effort we can still compare coordination in the two groups by checking whether $\underline{p}^j$ is greater or smaller than $(1 - \underline{p}^k)$ for two groups j and k.

in Table 3.2. The row player is assumed to have low ability, and the column player has high ability. We assume that $\bar{\theta}\underline{e} > \underline{\theta}\bar{e}$. Assuming, without loss of generality, that $\frac{D\theta}{c} > \alpha$, it turns out that this game has a unique equilibrium where the low ability worker plays $\bar{e}$, and the high ability worker plays $\underline{e}$.

Exploiting the fact that unconnected groups have relatively higher marginal costs from higher effort than connected groups, we show that under some conditions on α^C and α^U equilibrium selection in the connected group leads to higher group output (across the four possible ability matches) and lower wasted output, on average, than the unconnected group. However, though average individual output (across the four possible ability matches) is higher in the connected group for the low ability worker, for the high ability worker it is no different in connected and unconnected groups.[18]

Intuitively, note that the returns from putting in high effort depend on (a) the probability that the worker affects the outcome (i.e., is pivotal) – this is lower for the high ability type than the low ability type, given our assumption that $\bar{\theta}\underline{e} \geq \underline{\theta}\bar{e}$, (b) conditional on being pivotal, the returns from high effort – these are higher for high ability type than the low ability type. Finally, note that the marginal costs of high effort are lower for connected groups than unconnected groups. The difference in marginal costs together with (a) and (b) imply that group output is higher for connected groups because it is the low ability worker who determines group output more often than the high ability worker (i.e. low ability worker is pivotal and has lower cost in the connected group). High ability workers are not as affected by the difference in marginal costs because they are less likely to be pivotal, and, even when they are, they anyway have higher marginal benefits from high effort.

Claim 3.B.1 in Appendix 3.B shows that when the parameter values satisfy $\alpha^U > \frac{D\theta}{c} \geq \alpha^C$ then using risk dominance for equilibrium selection, the connected group has on average higher group output than the unconnected group, driven by the difference between α^C and α^U (and corresponding marginal costs). Moreover, wasted effort is lower in the connected group because the low ability worker is putting in high effort

[18]The full characterisation of equilibria along with proofs is provided in Appendix 3.B.

in the connected heterogeneous match, as opposed to low effort in the unconnected heterogeneous match ($\bar{\theta}\underline{e} - \underline{\theta}\bar{e} < (\bar{\theta} - \underline{\theta})\underline{e}$). However, the cost advantage may not be as important in the case of the homogeneous high ability match. Here the returns to high effort are higher since $\bar{\theta} > \underline{\theta}$, and each player is pivotal. Therefore, the cost difference between connected and unconnected games is less important leading to high group and individual output for both groups in this match. As a result, the high ability type chooses high effort in the homogeneous game, regardless of being connected or not, as long as $\alpha^U < \frac{D\bar{\theta}}{2c}$. Together with the fact the the high ability worker chooses low effort in the the heterogeneous match, we have that there is no difference in the effort (output) of the high ability worker when comparing connected and unconnected games. This leads to our two main predictions:

(1) *Socially connected groups coordinate on a higher group output on average (across all possible ability matches) than unconnected groups. Individual output is higher on average in connected groups, but only for low ability workers.*

(2) *Wasted output is lower on average (across all possible ability matches) in connected groups than unconnected groups.*

In our experiment, we introduce a lump sum bonus, B, which is given when team output is above a certain threshold, T. The bonus increases the marginal gain when moving from below threshold to the threshold output, thus it will increase incentives for higher effort at this point only. In general, it will have an effect only if the group was producing below the threshold, and the group has sufficiently low marginal costs. Therefore, whether socially connected groups perform differently from unconnected groups depends on the exact location of group output before the bonus. Given the nature of the coordination game, however, and the importance of beliefs on other workers' effort levels, a second effect of the bonus is to create a focal point for individuals to coordinate at. This leads to our third prediction:

(3) *A discrete lump sum bonus given above a threshold level of output will increase the output of groups/individuals who were producing below T before bonus, if it is sufficiently large relative to the marginal cost of effort. If the threshold creates a focal point, it implies,*

in addition, that it leads to an increase (decrease) in output of those groups/individuals who were producing below (above) T to begin with.

These results can be generalized to more than 2 workers and multiple effort levels (for proof and extensions see Appendix 3.B).

In the real world, there can be several mechanisms that can result in higher team output and better team coordination, as discussed previously. We therefore design a controlled lab-in-the field experiment described in detail next.

3.4 Experiment Design

Since our research question is how team productivity is influenced by workers' social connections and financial incentives, our lab-in-the-field experiment (Harrison and List (2004)) uses a 2x3 factorial, between-subject design. Each session consisted of a work team of 4 subjects of the *same* gender. In the Socially Connected treatment, the team had the same caste based network. In the Socially Unconnected treatment, the team members belonged to different caste based networks. In addition, we used two different incentive schemes – Piece Rate and Bonus (with two different framings—Gain Framing and Loss Framing). The experimental design is outlined in Table 3.3. We conducted both men and women only sessions in our experiment but focus on the men only sessions due to the cultural constraints in priming women's social connections.[19]

Subjects and recruiting The subjects of our experiment were garment factory workers, with at least primary education, in the NCR's garment factory hub. The experiment was conducted between May and July 2016. Recruiting

[19]We conducted 64 women only sessions (30 Socially Connected and 34 Socially Unconnected). We exclude these sessions from our analysis for two reasons. First, in India's patriarchal society women are typically referred to using a generic last name of *Devi* or *Kumari* (i.e. lady or girl) which would not signify their *jati* to other group members. Since caste is determined by birth and inter-caste marriages are virtually non-existent even today, we primed caste-based social connections by announcing a woman's first and generic last name followed by the first and last name of the man whose wife or daughter she was, and her residential address. Since our priming for women is indirect it may not be salient enough to activate her social connection. Second, safety concerns and restricted physical mobility of women due to which most women came to the sessions accompanied by other women they knew. Hence the probability of knowing someone even in the socially unconnected group was high for women.

pamphlets were distributed among the workers during our visits to their factories and residential clusters (see Figure 3A.1, translated from Hindi into English, in Appendix 3.A). The advertisement mentioned Rs.200 as participation fee which was about the daily wage of garment factory workers in our sample.[20] Workers registered over phone, and the information on their residential address, native state, caste, sub-caste or *jati*, and gender were collected at the time of registration.

We classified subjects on two dimensions to proxy for social networks. First, each subject was categorized according to his *jati* into one of the three main caste groups using the official categorization by his native state: (1) **L** type consisted of the historically marginalised *jatis* that belonged to Scheduled Castes (SC), the lowest in the social hierarchy; (2) **M** type constituted the other backward castes (OBC) that were socially and economically disadvantaged; and (3) the **H** type were subjects whose *jatis* belonged to the high castes.[21]

The second dimension of subject categorization was current residence. A residential cluster, in our context, represented a lane or *mohalla* in a particular worker colony. For instance, lane number 7 of Kapashera slum formed a residential cluster in our study. Visits to residential clusters during the study indicated that migrant workers of the same *jati* and native village resided in the same neighborhood. Hence the probability of workers sharing the same caste ethnicity and being socially connected as friends, relatives, and/or co-workers was high if they had the same residential address. To sum, social connections were determined by both caste and residential proximity in our experiment.

Subjects were given a specific date and time to visit the experiment site which was in a building in the garment manufacturing hub where most of these subjects worked. A subject was allowed to participate only once and was required to show his garment factory employment ID at the time of experiment.

[20]Note 1 USD was worth Rs.67 approximately in 2016.

[21]Both the L and M type typically have public sector jobs and political positions reserved for them under India's affirmative action policies (Deshpande (2013)). Factory jobs in the private sector are coveted by all castes and social groups of migrants in urban areas. Data collected by us from garment factories in the National Capital Region show that almost 50% of the workers were H type, 30% M type, and the remainder L type.

Task and incentives The experimental task involved subjects independently stringing beads on beading wires of a specific length in their private workstations partitioned by opaque curtains. To capture purely the effect of pre-existing social connections and beliefs about other workers in the team, neither communication amongst subjects nor information on the productivity of subjects was made public at any time during the experiment.[22] This design also conforms to the actual factory assembly line setting where workers have low probability of coordinating effort and output level through verbal communications or repeat physical interactions, as discussed in Section 2.

In each session the 4 subjects of a team were randomly assigned ID numbers from 1 to 4 which further mapped into their private workstations and their allotted bead colors - red, blue, green or white. Their ID numbers, workstation numbers, and bead colors were kept private to ensure anonymity of their individual performance throughout the experiment. The subjects were also informed that the identity of individual performances would not be disclosed at any point during or after the session. This was done to be able to assess the role of pro-social motivations on group coordination, as well as rule out threat of social sanction post-experiment as a determinant of effort on the assigned task. Note that since each session consisted of only one group we use the term “session" and “group" interchangeably.[23]

The experiment started with each subject being seated at his assigned workstation with a covered bowl containing beads of a single color and equal size along with a bunch of 20 cm long wires.[24] The subjects were told that their task was to string the wire with the beads in privacy such that the wire was fully covered with beads. The beaded strings of the four colors were to be combined to make bracelets by the experimenter at the end of the experiment. In other words, each bracelet – the team product – consisted of 4 strings of 4 colors, each string made by a subject. Thus, the minimum

[22]See experiment instructions, translated from Hindi into English, in Appendix II

[23]In each session there was one main instructor and an assistant instructor of different genders. Both instructors were graduate students whose caste categories were kept private throughout the experiment.

[24]The bowl was covered so the bead color could not be seen while the experimental instructions were being delivered.

number of strings (of a color) produced would determine the number of bracelets per team and thus the team output (see Figure 3A.2 in Appendix 3.A for a completed bracelet). By experimental design, therefore, group productivity was determined by the least productive worker of the team.

Once the task was explained and demonstrated using beads and a wire by the experimenter, information on the payoff functions were given. We used two financial incentive schemes – Piece Rate and Bonus (see Table 3.4). All the payoffs were based on the team output – the number of bracelets.[25] Under Piece Rate every subject received Rs.100 per completed bracelet produced by the team. For instance, if 5 red, 6 green, 4 blue, and 8 white strings were produced in a session the team's output would be 4 bracelets, and the payoff would be Rs.400 for each subject.

Our bonus incentive was motivated by the typical bonus schemes used in garment factories. Managements incentivize production of a target level of group output by offering a discrete bonus if the target is achieved by the line. In view of this factory setting, our experimental Bonus scheme offered each subject a bonus of Rs.150 above and beyond the Rs.100 piece rate if they reached a group output of 5 or more bracelets. This design feature was motivated by our finding in our pilot experiment, using Piece Rate payments, that the median performance of a team was 4 bracelets. We, therefore, used 5 bracelets as the threshold for the Bonus scheme. Given that the average daily wage of the subjects was approximately Rs.200, the bonus incentive was high powered. Since such a scheme could also create a focal level of output, it provided us with a weak test of the impact of financial incentives on raising group output to a feasible level.

The Bonus framing used was different, however. Under Bonus with Gain Framing, it was announced that if their team made 5 or more bracelets, each team member would receive a coupon of Rs.150 which could be encashed at the time of payment. In contrast, under Bonus with Loss Framing, for instilling a sense of loss, each subject

[25] Although workers receive fixed wages based on their daily attendance at work in most garment factories in NCR, in the real world factory setting the presence of the assembly line supervisor implicitly creates team based productivity incentives, as the supervisor is interested in line level output.

was given a coupon equivalent to Rs.150. But if their team made less than 5 bracelets the Rs.150 coupon would be taken away so they would lose this extra money and only get paid Rs.100 for each bracelet. Every subject in his workstation was given a payoff table corresponding to the assigned incentive scheme. The experimenter gave specific examples that elucidated the calculation of individual payoffs. Before proceeding with the experiment, each subject was provided with a sheet and a pen to answer several questions to ensure their understanding of the payoff calculation.

Social connections To study how team productivity is influenced by workers' social connections at work, we manipulated the caste and residence composition of the 4-person team in the sessions. Subjects were randomly assigned into the Socially Connected and the Socially Unconnected treatments. In a Socially Connected session, all 4 subjects belonged to the same caste category and currently resided in the same residential cluster to ensure that they shared similar social backgrounds. Specifically, they belonged either to the same or similar *jati* in the low caste category (**L** type), the middle caste category (**M** type), or the high caste (or **H** type). In contrast, a Socially Unconnected session consisted of subjects belonging to different caste categories and different residential clusters. We used the following criteria in selecting four subjects for the Socially Unconnected sessions – one L, one M, and one H type. The fourth subject could belong to any of the three types.[26]

One crucial part of our design was to make the subjects aware of the caste composition and thereby the strength of social connections of their work team. Since in India the last name of a person reflects the *jati* (i.e., sub-caste) of an individual, this was done through public announcements of each subject's name and residential address. After ensuring that the task and payoffs had been clearly understood by the subjects, the experimenter announced in public the first and last name as well as the residential address of each subject with the workstation curtains drawn apart so that the subjects could see each other. Each subject raised his hand when the name was

[26]For instance, a socially connected session of M type may have consisted of 4 Yadav *jati* or 3 Yadav and 1 Kurmi *jati* subjects, all of who are 'other backward castes' in the state of Uttar Pradesh. The within session variation in the *jati* of the 4 subjects in the socially connected sessions was 0.37 as opposed to 1.23 in the Socially Unconnected sessions, different at 1% significance level.

called.[27] Note that the degree of social connections of the team was made public in both the Socially Connected and the Socially Unconnected treatments. Subjects were not matched solely on caste identity but on both caste and residential status. Hence we made social connections, rather than identity, salient.[28]

Procedure Once the task was explained and the experimenter announced the subjects' names and addresses, curtains were drawn and subjects remained in separate, adjacent work stations during the rest of the experiment. Subjects were then asked to remove the cover on the bowls containing their allotted color of beads and practice the beads stringing task with one string. Thereafter, 10 minutes were given to subjects to string beads in as many wires as they desired. After 10 minutes, beaded wires were collected one by one by the experimenter in an opaque envelope and kept in front of the workstations on a desk.

Subjects were then requested to complete a post-experiment survey on additional information such as age, caste, religion, employment status, relationship (if any) with their team members, and beliefs about the productivity of co-workers they knew before the experiment.[29]. Once all four subjects completed their questionnaires, the partition curtains were drawn apart. The envelopes with the beaded strings were opened one by one, and the number of complete strings of each color was counted without revealing each subject's performance. The number of bracelets produced by the team was determined. Subjects received their payment in cash and were dismissed.

As shown in Table 3.3, we conducted 67 independent sessions consisting of male subjects, including 33 Socially Connected sessions and 34 Socially Unconnected sessions. Among these sessions, 16 used Piece Rate, and 51 used the Bonus Incentive including 25 sessions with Gain Framing and 26 sessions with Loss Framing. Between-subject design was used, hence no subject participated in more than one session. The

[27] In all sessions the main experimenter followed a prepared script and said the following:"Now I will announce your name and your residential address. As I call out your names please raise your hand. If there is any error in the announcement, please tell us."

[28] Unlike some previous studies that use subjects' names as identity prime (Hoff and Pandey (2006), Afridi et al. (2015b)) this study uses public announcement of names and residential addresses to ensure common knowledge of the caste composition and related social connections among the team members.

[29] Post-experiment questionnaires, translated from Hindi into English, are attached in Appendix III

experiment lasted about one hour. The average individual output was 4.5 beaded wires, and the average group output was 3.5 bracelets. The average payment was Rs.565.8 (including the Rs.200 participation fee) which was more than twice the average daily wage of the subjects.[30]

3.5 Data, Methodology, and Results

3.5.1 Data

The summary statistics from the post-experiment survey are shown in Table 3.5. Our subjects were approximately 29 years old with almost 89% Hindu. The proportion of Hindus was comparable across treatments.[31] Marginally fewer men had completed high school or more in the Socially Unconnected treatments. Almost the entire sample consisted of migrants from outside Delhi of which more than $\frac{1}{2}$ had migrated from the north-eastern state of Bihar. We were successful in recruiting subjects who were currently working (more than 97%), 98.5% of whom were currently employed in garment factories. Subjects' perception of task difficulty did not differ by treatment. Subjects knew almost 2 (1.9 out of possible 3) co-workers by name in the Socially Connected treatments, significantly more than in the Socially Unconnected treatments (by design). 93% (31%) of the known subjects had the same state of origin, 54% (0%) came from the same state-district and 90% (0%) shared their *jati* in the Socially Connected (Unconnected) treatments.[32] There was no variation in the caste group (i.e. H, M and L) of subjects within the Socially Connected treatments as designed. The experiment design was, therefore, effective in creating the connected and unconnected groups.

[30]See Appendix 3.C for discussions of the conduct and findings of women only sessions.

[31]In this study, 11% of our subjects were Muslim. Of these, 53% were M type while the remaining were H type. Although the caste system is a feature of Hinduism, social identities are strong even amongst religious minorities who are often SCs and STs who converted to Islam or Christianity. In the Socially Connected treatment sessions we held religion constant. Hence, M (H) Muslim subjects were matched with M (H) Muslims. Nevertheless, throughout our analysis we control for religion. Our results are also robust to restricting the sample to Hindus.

[32]The co-subjects known by name in the Socially Connected treatments were most often described as neighbor (94%), followed by friend (84%), co-worker (32%), and relative (30%) in the post-experiment survey which allowed for multiple relationships between subjects (see Appendix III).

Overall, Table 3.5 indicates that most of the average subject characteristics are comparable across treatments, which suggests successful randomization of subjects into treatments. In our analyses we, nevertheless, control for the observable characteristics of the subjects that either are different across treatments or may influence the outcomes in our study.[33]

We are interested in two categories of outcomes – output and coordination. They are summarized in Figure 3.1 for the Socially Connected and Socially Unconnected treatments, respectively. Output is measured at the individual level by the number of completed wires (Figure 3.1(a)) and at the group level by the minimum individual performance in each group (Figure 3.1(b)). Coordination is measured at the individual level by excess individual output (which is individual output minus the group output, Figure 3.1(c)) and at the group level by within-group output dispersion (which is the standard deviation of individual completed wires within the group, Figure 3.1(d)). Since an individual's output above and beyond the minimum output of his group is not counted toward the group output any excess individual output would be wasted. Therefore, lower level of excess individual output (or wasted output) or within-group output dispersion signifies better coordination.

Figures 3.1(a)-(b) show that subjects respond positively to social connectedness by producing a higher level of output both individually ($p < 0.10$) and as a group ($p < 0.05$) in the Socially Connected treatments than the Unconnected ones. Figures 3.1(c)-(d) show that they also coordinate better, resulting in lower excess output and within-group output dispersion ($p < 0.01$ for both cases), when they are socially connected, rather than unconnected, with their co-workers.[34]

[33] In Table 3A.1, Appendix 3.A, we show the average characteristics of subjects by the financial incentive.

[34] In the Socially Unconnected (Connected) sessions with piece rate, more than 52% (25%) of subjects and more than 88% (71%) of groups produced less than 5 bracelets. 36% of groups made exactly 4 bracelets. Hence there was substantive scope for the lump-sum bonus to raise the average group output to or above 5 bracelets.

3.5.2 Empirical methodology and results

We use the following OLS specification to study the impact of social and financial incentives on the above mentioned outcomes:

$$Y_{is} = \alpha_0 + \alpha_1 \textit{Socially Connected}_s + \alpha_2 \textit{Bonus Incentive}_s + \alpha_3 \mathbf{Z}_{is} + \epsilon_{is} \tag{3.1}$$

The dependent variable is Y_{is}, i.e., individual *i's* output or excess output in session *s*, for the individual-level analysis. 'Socially Connected' is a dummy variable for the Socially Connected treatments (with the Socially Unconnected treatments in the omitted category). 'Bonus Incentive' is the treatment dummy variable for the high powered bonus incentive (with Piece Rate in the omitted category).[35] **Z** is a vector of individual characteristics such as separate dummy variables for the H and M caste categories (with L in the omitted category), age, religion, native state, employment status, and education. The coefficient α_1 gives an estimate for the average effect of being in a socially connected group on the individual or group outcomes relative to the socially unconnected group, unconditional on the financial incentives. Similarly, the coefficient α_2 provides an estimate of the average effect of the Bonus Incentive relative to Piece Rate, unconditional on the social incentives. The standard errors are clustered at the session (i.e. the group) level for individual-level outcomes.

Equation 3.1 can be further augmented by incorporating the interaction terms between the social and financial incentives:

$$\begin{aligned} Y_{is} = {} & \beta_0 + \beta_1 \textit{Socially Connected}_s + \beta_2 \textit{Bonus Incentive}_s \\ & + \beta_3 \textit{Socially Connected}_s * \textit{Bonus Incentive}_s + \beta_4 \mathbf{Z}_{is} + \epsilon_{is} \end{aligned} \tag{3.2}$$

Note that subscript *i* drops out for the group-level analysis (i.e., group *s*'s output or within-group output dispersion) in both equations 3.1 and 3.2.

Table 3.6 reports the results of equation 1 on individual and group output. We

[35] We find little evidence on the effect of the framing and thus pool the data in the Bonus Gain and Loss framing treatments in the analysis.

find that although social connectedness leads to a positive but insignificant effect on individual output ($\alpha_1 = 0.114$, $p > 0.10$ in column 1), it has a positive and statistically significant effect on group output ($\alpha_1 = 0.574$, $p < 0.05$ in column 2). Since these estimates are unconditional on the financial incentives, they show that for the piece rate and bonus schemes on average, being in a socially connected group increases *qualitatively* the individual outgroup by 0.114 bracelets (or 2.6%) and increases significantly the group output by 0.574 bracelets (or 18%).[36]

Table 3.7 focuses on coordination. We find that the coefficient estimate of 'Socially Connected' is -0.457 for excess individual output ($p < 0.01$ in column 1) and -0.325 for within-group output dispersion ($p < 0.05$ in column 2). That is, on average across the two financial incentives, social connectedness leads to 39% decrease in the wasted output and 31% decrease in the within-group dispersion. These findings indicate that subjects coordinate significantly better when they are with co-workers with whom they feel more socially connected.[37]

The findings in Table 3.6 and Table 3.7, therefore, validate the theoretical predictions 1 and 2.[38] They lead to Results 3.1 and 3.2.

Result 3.1: Being in a socially connected group leads to a significant increase in the group output and only a qualitative, but statistically insignificant, increase in the individual output.

Result 3.2: Being in a socially connected group improves within-group coordination.

Note that the coefficients of 'Bonus Incentive' are statistically insignificant throughout in Tables 3.6 and 3.7, suggesting that higher financial incentives neither increase

[36]These estimates are lower for individual output but higher for group output, compared to the 11-16 percentage point increase suggested by the factory data, given average minimum line efficiency of 5% in Chapter 2.

[37]Our results are unaltered when we include additional control variables in the analysis, e.g. dummy variables for "having done similar kind of task earlier" and the months when the experiment was conducted. These robustness checks with the estimates of all the explanatory variables are reported in Table 3A.3 and Table 3A.4, Appendix 3.A. The conclusions are unchanged when we bootstrap the standard errors.

[38]We explore heterogeneity of the impact of social connectedness by caste category in Table 3A.5 in Appendix 3.A. Interestingly, the L type respond significantly to being socially connected by raising individual output. The H type significantly improve their group output and reduce within-group dispersion when they are socially connected than when unconnected.

(individual or group) output nor improve coordination within a group, irrespective of social connectedness amongst workers. Next, we analyze the effect of social connectedness conditional on the financial incentives using Equation 3.2. The results on output are reported in Table 3.8. The coefficient of 'Socially Connected' β_1 indicates that under the piece rate incentive, social connectedness leads to an increase in individual output by 0.561 bracelets ($p < 0.10$, column 1) and an increase in group output by 1.172 bracelets ($p < 0.05$, column 2), relative to being in a socially unconnected group. Conditional on the high powered bonus incentive, however, the impact of social connectedness is statistically insignificant for individual output ($\beta_1 + \beta_3 = -0.029$, $p = 0.845$, column 1) and for group output ($\beta_1 + \beta_3 = 0.407$, $p = 0.170$, column 2). Therefore, the positive impact of social connectedness on group output summarized in Result 1 is mainly driven by its impact under Piece Rates. Interestingly, we also find that conditional on social connectedness, individual output may be *lower* under the bonus incentive than under piece rate ($\beta_2 + \beta_3 = -0.411$, $p = 0.052$, column 1 of Table 3.8), and the same pattern seems to hold for the group output ($\beta_2 + \beta_3 = -0.869$, $p = 0.102$, column 2).[39]

To evaluate these results related to our theoretical prediction 3, we estimate the impact of the Bonus relative to two subsamples under Piece Rate: (1) less productive individuals/groups, i.e. those who produce less than the focal point of 5 completed wires/bracelets in Piece Rate, and (2) more productive ones, i.e. those who produce 5 or more in Piece Rate. We compare these two subsamples of Piece Rate to Bonus, respectively, and conduct the analysis as in Table 3.9. This comparison allows us to infer how the output of the less (more) productive individuals/groups would be affected had they been offered the Bonus, conditional on the degree of the group's social

[39]In Table 3A.6, Appendix 3.A, we estimate Equation 3.2 for the coordination outcomes. Column 1 shows that the excess individual output is lower and hence individual coordination is better in the Socially Connected treatment than in the Socially Unconnected treatment under Piece Rate ($\beta_1 = -0.275$ in column 1, $p > 0.10$) and conditional on the Bonus Incentive ($\beta_1 + \beta_3 = -0.515$, $p = 0.002$). It suggests that social connectedness effectively reduces workers' wasted output and promotes their coordination, but insignificantly under high powered financial incentives ($\beta_3 = -0.239$ in column 1, $p > 0.10$). Column 2 of Table 3A.6 further shows that the impact of social connectedness is along the same lines for the within-group output dispersion ($\beta_1 = -0.359$, $p > 0.10$ for Piece Rate; conditional on the Bonus $\beta_1 + \beta_3 = -0.316$, $p = 0.029$ but $\beta_3 = 0.043$, $p > 0.10$ for Bonus).

connectedness. Table 3.9 shows that, indeed offering the Bonus incentive can increase individual output significantly ($\beta_2 = 1.165$, $p = 0.040$, column 1) and group output insignificantly ($\beta_2 = 0.111$, $p = 0.774$, column 2) when we compare them to those individuals or groups whose output was less than 5 under Piece Rate. The impact of the Bonus relative to those producing 5 pieces or more under Piece Rate is the opposite ($\beta_2 = -0.894$ for individual output, $p = 0.000$, column 3; $\beta_2 = -1.736$ for group output, $p = 0.053$, column 4). Note that the above effect of the Bonus relative to Piece Rate does not depend on the degree of social connnectedness, however, as β_3 is statistically insignificant for all columns of Table 3.9. They highlight the fact that the Bonus, as devised by managements to incentivize workers, could serve as a double-edged sword – increasing the productivity of less productive workers/groups but lowering the productivity of those producing above the threshold. These findings in Table 3.9 lead us to our final result.

Result 3.3: In line with theoretical prediction 3, the bonus incentive increases (decreases) individual output significantly and group output insignificantly, relative to individuals/groups whose output was below (above) the threshold level under piece rate, irrespective of social connectedness of subjects.

To summarize, our main results show that socially connected groups produce higher group output due to better coordination, but not higher individual output, than the unconnected groups, as predicted by our theoretical model. Introducing a lump-sum bonus, on average, does not enhance the advantage that the socially connected groups have over the socially unconnected, since it creates a focal point for all workers to coordinate on. A bonus of this kind, therefore, is likely to reduce variation in productivity across teams but will only lead to higher overall firm output if it is aimed sufficiently high.[40]

[40] We did not find any consistent effect of the Bonus on group coordination around the threshold. Further, Table 3A.7 in Appendix 3.A shows little effect of the Bonus framing. The only exception is that the Bonus with Loss framing lowers individual output, relative to Piece Rate, for the socially connected groups (column 1, $\beta_4+\beta_5 = -0.462$, $p = 0.037$). This may be because the bonus incentive is offered based on the group performance, rather than individual performance as in previous field experiments. Our finding adds to the literature which shows mixed evidence on the framing of incentives, with a positive impact in some (e.g., Hossain and List (2012)) and a small effect in other studies (e.g., List and Samek

3.5.3 Discussion of results

As elucidated by the theoretical model, group contingent social preferences among co-workers in socially connected teams can plausibly explain our results. When workers know that their co-workers belong to the same network, they believe that others are going to put in high effort ($\underline{p}$ is lower). As a result, their own incentive to put in high effort increases. We test for these beliefs by eliciting expected productivity of co-workers. In our post-experiment survey we asked subjects to state how many beaded wires they expected a co-worker, whom they knew by name before the experiment, to make in the allotted 10 minutes. Subjects overestimated the productivity of the co-workers they knew by name before the experiment. The difference between the expected and actual co-worker output was 0.40 ($p < 0.001$) for 248 unique connections in the Socially Connected treatments.[41] This provides some suggestive evidence for our explanation. In addition, survey data from a census of workers employed in two garment factories in the catchment area of our experiment indicates greater levels of pro-social motivation between socially connected workers. Specifically, 32% (24%) of workers who have a co-worker with whom they are socially connected (viz. neighbor/relative/fellow villager), as opposed to 16% (18%) of those with a co-worker friend who they met on the job recently, report lending Rs.500 or more to that friend (asked for help in medical emergency.)

There may be alternative explanations for our findings, however. One may be concerned that workers in the connected groups may have more information on others' abilities; such informational advantage may improve group coordination. On the one hand, it is important to note that informational advantage is not a necessary condition for higher group output and coordination in our theoretical model. Pro-social motivations can lead to better outcomes for the connected groups even in the absence of informational advantage. On the other hand, our experiment was designed to minimize the potential confounds due to informational advantage on ability. Specifically,

(2015)).

[41]The number of connections in the Socially Unconnected treatments were negligible, by design.

it involved a real-effort task that subjects had not engaged in collectively before, and thus it was difficult to guess others' abilities even among the connected co-workers. The correlation between the predicted and actual output for the connected workers is 0.175 in the Socially Connected treatments – economically small, albeit, statistically significant ($p < 0.001$). Hence we cannot conclude, either theoretically or empirically, that knowledge about co-worker ability *alone* is the driver of both higher group output and better coordination seen in the connected groups in our experiment.

Another possible explanation is that our experimental design merely sorts on ability, i.e., if L, M, and H types have differential abilities the socially connected groups would produce both higher group output and show better coordination just by experimental design. But we do not find significant differences in productivity (or ability) by caste types either in our experiment (Socially Unconnected treatments) or in the real world factory data (see Table 3A.2 in Appendix 3.A). Moreover, our results are robust after we control for ability by including a dummy variable for whether the subject has previous experience of performing the assigned task.[42]

Finally, it may be argued that group based incentives together with the potential threat of sanctions for low effort in socially connected groups might also lead to higher group output. If socially connected subjects have a better idea of who is holding down output in their group, then such subjects may put in higher effort due to fear of punishment by the team, raising both group output and improving coordination. Our experimental design guards against this possibility since the information on individual performance was kept private throughout the experiment, and subjects were informed so upfront. Furthermore, as discussed above, workers' expectations of their co-workers' effort were only weakly correlated with the actual individual output in the connected groups. By ruling out these alternative explanations, we, therefore, conclude that our experimental helps us identify the role of group-contingent social preferences among connected co-workers.

[42]As elucidated earlier, our experiment design did not prime group identity *per se*, but rather gave information on co-subjects' social connections. Hence our results do not speak purely to social identity as a possible mechanism, unlike previous studies such as Hjort (2014), Chen and Li (2009), and Chen and Chen (2011).

3.6 Conclusion

We conduct a lab-in-the-field experiment to study the impact of caste-based social connections on output and coordination among workers engaged in a minimum effort game. Our results suggest that being socially connected to co-workers significantly improves group coordination and output though not individual productivity. Further, we find that high powered incentives such as a lump-sum bonus may not lead to higher group productivity and coordination, regardless of social connectedness among co-workers.

These findings can be explained by pro-social motivations among socially connected workers. However, in our survey of garment factory workers we find that 16% of workers report having no friends in the workplace, while the average worker reports less than 2 co-workers as friends. These data and our findings underline the need for managements to create avenues for greater social interactions among co-workers at the work place to enhance productivity.

Our research not only connects the laboratory literature on group coordination with the field experiments on labor productivity, it adds to the growing body of work on the relevance of personnel economics within firms to economic growth. Our results provide strong evidence of the role of co-worker relationships in resolving coordination issues inside the workplace, particularly in contexts where average worker productivity is poor, as is true in most low income countries. Future research could study how worker coordination evolves over time in teams with heterogeneous ability and social connectedness to better understand why some firms become more productive over time and others don't.

3.7 Tables

Table 3.1: Minimum effort game with homogeneous ability type

	$\bar{e}$	$\underline{e}$
$\bar{e}$	$D\theta\bar{e} - c\bar{e}$ $D\theta\bar{e} - c\bar{e}$	$D\theta\underline{e} - c(\alpha\bar{e} + (1-\alpha)\underline{e})$ $D\theta\underline{e} - c(\alpha\underline{e} + (1-\alpha)\bar{e})$
$\underline{e}$	$D\theta\underline{e} - c(\alpha\underline{e} + (1-\alpha)\bar{e})$ $D\theta\underline{e} - c(\alpha\bar{e} + (1-\alpha)\underline{e})$	$D\theta\underline{e} - c\underline{e}$ $D\theta\underline{e} - c\underline{e}$

Table 3.2: Minimum effort game with heterogeneous ability type

	$\bar{e}$	$\underline{e}$
$\bar{e}$	$D\underline{\theta}\bar{e} - c\bar{e}$ $D\underline{\theta}\bar{e} - c\bar{e}$	$D\underline{\theta}\bar{e} - c(\alpha\bar{e} + (1-\alpha)\underline{e})$ $D\underline{\theta}\bar{e} - c(\alpha\underline{e} + (1-\alpha)\bar{e})$
$\underline{e}$	$D\underline{\theta e} - c(\alpha\underline{e} + (1-\alpha)\bar{e})$ $D\underline{\theta e} - c(\alpha\bar{e} + (1-\alpha)\underline{e})$	$D\underline{\theta e} - c\underline{e}$ $D\underline{\theta e} - c\underline{e}$

Note: The row player is assumed to have low ability ($\underline{\theta}$), and the column player is high ability ($\bar{\theta}$).

Table 3.3: Experiment design and sample

	Number of sessions			Number of subjects
Financial Incentive	**Socially Connected**	**Socially Unconnected**	**All**	
Piece Rate	7	9	16	64
Bonus	26	25	51	204
Bonus with Gain Framing	13	12	25	100
Bonus with Loss Framing	13	13	26	104
	33	34	67	268

Note:'Bonus' includes both 'Bonus with Gain Framing' and 'Bonus with Loss Framing'. The break-up of bonus sessions by framing is described in rows 3 and 4.

Table 3.4: Financial incentives and payoffs

Number of bracelets produced by group	Subject payoff (Rs.)	
	Piece Rate	**Bonus**
1	100	100
2	200	200
3	300	300
4	400	400
5	**500**	**500 + 150 =650**
6	600	600 + 150 =750
7	700	700 + 150 =850
...	...	...

Notes: Each subject was given Rs.200 as participation fees in all sessions. As depicted above, the payment scheme was the same in Bonus with Gain Framing and Bonus with Loss Framing. The only difference was that in the Bonus with Loss Framing the payment schedule was presented to subjects in the reverse order, i.e. starting with 7 or more bracelets and moving down to 1 bracelet to produce a sense of 'loss' if they did not meet the threshold of 5 bracelets.

Table 3.5: Summary statistics by social connectedness

Characteristics	**Socially Connected**	**Socially Unconnected**	Difference
	[N=132]	[N=136]	
	(1)	(2)	(2)-(1)
Age (years)	28.341	29.022	0.681
	(0.583)	(0.594)	(0.833)
Hindu	0.878	0.897	0.018
	(0.028)	(0.026)	(0.039)
Married	0.727	0.713	-0.014
	(0.039)	(0.039)	(0.055)
Completed high school or more	0.333	0.228	-0.105*
	(0.041)	(0.036)	(0.055)
Migrant from Bihar	0.598	0.691	0.092
	(0.042)	(0.040)	(0.058)
Currently employed	0.977	0.971	-0.007
	(0.013)	(0.014)	(0.020)
Found task easy	0.742	0.654	-0.088
	(0.038)	(0.041)	(0.056)
Knew at least one team member by name	0.848	0.080	-0.767***
	(0.031)	(0.023)	(0.039)
Number of co-workers known by name	1.894	0.125	-1.769***
	(0.098)	(0.041)	(0.105)
Caste dispersion in a session	0.000	1.184	1.184***
	(0.000)	(0.026)	(0.027)

Note: Standard errors reported in parentheses. *t*-tests of differences reported in column 3. Significant at *10%, **5%, and ***1%.

Table 3.6: Impact of group composition on output(unconditional estimates)

	Individual Output	Group Output
	(1)	(2)
Socially Connected (α_1)	0.114	0.574**
	(0.129)	(0.261)
Bonus Incentive (α_2)	-0.062	-0.353
	(0.194)	(0.315)
Constant	5.605***	6.186***
	(0.592)	(1.873)
Mean for Socially Unconnected	4.375	3.206
Number of observations	268	67
Number of sessions	67	67
R^2	0.102	0.196

Note: In columns 1 the dependent variable is *individual* output defined as the number of completed wires made by a subject. In column 2 the dependent variable is *group* output defined as the number of bracelets (i.e., the minimum number of completed wires) made by a group. 'Bonus Incentive' is a dummy that equals 1if the bonus was offered to the group and 0 if the incentive was piece rate. Other control variables include age, Hindu, dummy for H type, dummy for M type, and dummies for primary schooling complete, native state Bihar and currently employed. The estimates of these control variables are omitted for brevity but are similar to those in the analysis of robustness checks reported in Table 3A.3 in Appendix 3.A. Standard errors (clustered at the session level in column 1) are reported in parentheses. Significant at *10%, **5%, and ***1%.

Table 3.7: Impact of group composition on coordination (unconditional estimates)

	Excess Individual Output	Within-Group Output Dispersion
	(1)	(2)
Socially Connected (α_1)	-0.457***	-0.325**
	(0.154)	(0.124)
Bonus Incentive (α_2)	0.112	-0.027
	(0.183)	(0.15)
Constant	1.411***	0.757
	(0.524)	(0.89)
Mean for Socially Unconnected	1.169	1.056
Number of observations	268	67
Number of sessions	67	67
R^2	0.087	0.132

Note: In column 1 the dependent variable is the excess individual output defined as individual output minus group output. In column 2 the dependent variable is within-*group* output dispersion defined as the standard deviation of individual output within a group. 'Bonus Incentive' is a dummy that equals 1 if the bonus was offered to the group and 0 if the incentive was piece rate. Other control variables include age, Hindu, dummy for H type, dummy for M type, and dummies for primary schooling complete, native state Bihar and currently employed. The estimates of these control variables are omitted for brevity but are similar to those in the analysis of robustness checks reported in Table 3A.4 in Appendix 3.A. Standard errors (clustered at the session level in column 1) are reported in parentheses. Significant at *10%, **5%, and ***1%.

Table 3.8: Impact of group composition on output by incentive (conditional estimates)

	Individual Output	Group Output
	(1)	(2)
Socially Connected (β_1)	0.561*	1.172**
	(0.331)	(0.549)
Bonus Incentive (β_2)	0.179	-0.104
	(0.300)	(0.372)
Bonus Incentive x Socially Connected (β_3)	-0.590	-0.765
	(0.383)	(0.619)
Constant	5.465***	6.378***
	(0.584)	(1.871)
Mean for Socially Unconnected	4.375	3.206
Number of observations	268	67
Number of sessions	67	67
R^2	0.102	0.196

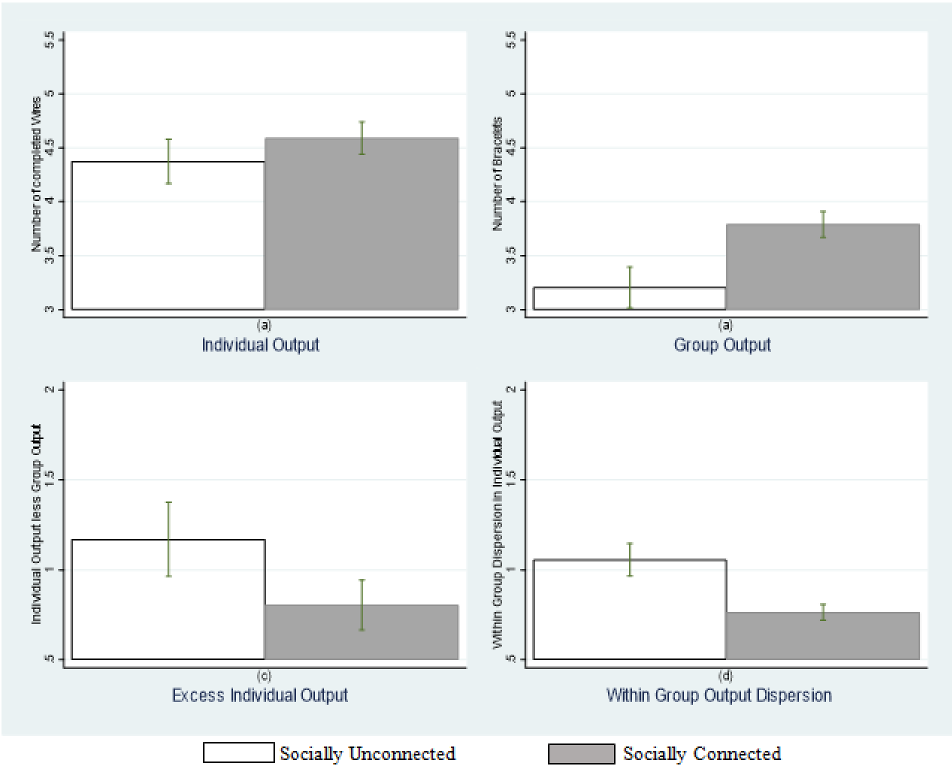
Note: as elucidated in Table 4.6 above.

Table 3.9: Impact of group composition on output by incentive (conditional estimates)

	Relative to less than 5 output in Piece Rate		Relative to 5 or more output in Piece Rate	
	Individual Output	Group Output	Individual Output	Group Output
	(1)	(2)	(3)	(4)
Socially Connected (β_1)	0.420	1.035*	-0.208	0.365
	(0.408)	(0.570)	(0.189)	(1.217)
Bonus Incentive (β_1)	1.165***	0.111	-0.894***	-1.736*
	(0.394)	(0.383)	(0.147)	(0.874)
Bonus Incentive x Socially Connected (β_1)	-0.431	-0.621	0.227	0.049
	(0.456)	(0.637)	(0.259)	(1.238)
Constant	4.519***	6.262***	6.569***	8.062***
	(0.530)	(1.825)	(0.591)	(2.099)
All controls	Yes	Yes	Yes	Yes
Number of observations	230	64	242	54
R^2	0.216	0.207	0.205	0.315

Note: Note: as elucidated in Table 4.6. In column 1 (column 3) we drop *individuals* who produced 5 or more (less than 5) beaded wires under Piece Rate from the sample. In column 2 (column 4) we drop *groups* that produced 5 or more (less than 5) bracelets under Piece Rate from the sample. Standard errors clustered at the session level are reported in parentheses (except in columns 2 and 4 where the unit of analysis is the group). Significant at *10%, **5%, and ***1%.

Figure 3.1: Output and coordination by group composition



Note: Mean *individual* output is 4.481 strings, mean *group* output is 3.492 bracelets, mean excess *individual* output is 0.911, mean with-in *group* output dispersion is 0.995.

3.8 Appendices

3.A Additional results

Table 3A.1: Summary statistics by financial incentive

Characteristics	**Piece Rate**	**Bonus with Gain Framing**	Bonus with Loss **Framing**
	[N=64]	[N=100]	[N=104]
	(1)	(2)	(3)
Age (years)	28.44	28.86	28.67
	(0.846)	(0.654)	(0.701)
Hindu	0.78	0.88	0.96
	(0.052)	(0.033)	(0.019)
Married	0.69	0.75	0.71
	(0.058)	(0.043)	(0.045)
Competed high school or more	0.20	0.27	0.34
	(0.051)	(0.045)	(0.047)
Migrant from Bihar	0.66	0.69	0.60
	(0.060)	(0.046)	(0.048)
Currently employed	0.97	0.99	0.96
	(0.022)	(0.010)	(0.019)
No. of beaded wires	4.53	4.46	4.47
	(0.157)	(0.105)	(0.092)
Found task easy	0.72	0.72	0.66
	(0.057)	(0.045)	(0.047)
Knew at least one team member by name	0.42	0.44	0.50
	(0.062)	(0.050)	(0.049)
Number of co-workers known by name	0.77	0.96	1.17
	(0.129)	(0.125)	(0.129)
Caste dispersion in a session	0.93	0.76	0.78
	(0.052)	(0.055)	(0.054)

Note:Standard errors are reported in parentheses.

Table 3A.2: Average productivity by caste

	Factory data		Experiment data	
	Number of worker -days	Efficiency	Number of subjects in socially unconnected group	Number of completed wires
All	1744	0.312	136	4.375
		(0.005)		(0.104)
L	384	0.308	30	4.300
		(0.010)		(0.215)
M	543	0.300	60	4.550
		(0.009)		(0.131)
H	817	0.321	46	4.196
		(0.007)		(0.212)

34,641 person days map into 1744 workers in our factory data. No significant differences(at 5% level of significance) are found in average efficiency of workers by caste. The *p*-values of all pair-wise differences range from 0.06 to 0.58 in the factory data and 0.14 to 0.74 in the experiment data.

Table 3A.3: Effect of group composition on output with additional controls

	Individual Output	**Group Output**
	(1)	(2)
Socially Connected	0.117	0.585**
	(0.129)	(0.263)
Bonus incentive	-0.046	-0.315
	(0.193)	(0.354)
Age	-0.038***	-0.04
	(0.012)	(0.043)
Married	0.098	0.092
	(0.171)	(0.653)
Hindu	-0.444	-1.229**
	(0.291)	(0.542)
Currently employed	0.025	-0.238
	(0.484)	(1.404)
Primary education complete	0.278	-0.617
	(0.169)	(0.693)
Migrant from Bihar	0.277**	0.478
	(0.128)	(0.367)
Done similar task earlier	-0.414	-0.912
	(0.262)	(0.588)
June	0.000	0.000
	(.)	(.)
July	-0.124	-0.203
	(0.149)	(0.282)
H type	-0.380	-1.089
	(0.236)	(0.692)
M type	0.098	-0.241
	(0.185)	(0.552)
Constant	5.777***	6.296***
	(0.615)	(1.982)
Number of observations	268	67
Number of sessions	67	67
R^2	0.122	0.233

Note: Standard errors (clustered at the session level in column 1) are reported in parentheses. Significant at *10%, **5%, and ***1%.

Table 3A.4: Effect of group composition on coordination with additional controls

	Excess Individual Output	Within-Group Output Dispersion
	(1)	(2)
Socially Connected	-0.462***	-0.329***
	(0.156)	(0.123)
Bonus incentive	0.053	-0.008
	(0.207)	(0.166)
Age	-0.030***	-0.124
	(0.010)	(0.305)
Married	0.148	-0.124
	(0.166)	(0.305)
Hindu	0.145	0.288
	(0.274)	(0.254)
Currently employed	0.047	-0.028
	(0.476)	(0.656)
Primary education complete	0.462**	0.201
	(0.192)	(0.324)
Migrant from Bihar	0.091	-0.095
	(0.163)	(0.171)
Done similar task earlier	-0.077	0.580**
	(0.233)	(0.275)
June	0.000	0.000
	(.)	(.)
July	0.098	0.059
	(0.160)	(0.132)
H type	-0.019	0.198
	(0.198)	(0.324)
M type	0.151	0.145
	(0.168)	(0.258)
Constant	1.506***	0.572
	(0.525)	(0.927)
Number of observations	268	67
Number of sessions	67	67
R^2	0.092	0.198

Note: Standard errors (clustered at the session level in column 1) are reported in parentheses. Significant at *10%, **5%, and ***1%.

Table 3A.5: Impact of group composition on effort and co-ordination conditional on caste

	Individual Output	Group Output	Excess Individual Effort	Within-Group Output Dispersion
	(1)	(2)	(3)	(4)
Socially Connected (α_1)	0.445*	0.004	-0.403*	0.650
	(0.247)	(1.260)	(0.222)	(0.589)
H type (α_2)	-0.219	-3.178*	-0.006	1.874**
	(0.325)	(1.826)	(0.251)	(0.854)
M type (α_3)	0.166	-0.005	0.164	0.842
	(0.240)	(1.492)	(0.248)	(0.698)
H type x Socially Connected symbol (α_4)	-0.568	2.115	-0.0435	-1.804**
	(0.460)	(1.865)	(0.328)	(0.872)
M type x Socially Connected (α_5)	-0.294	-0.272	-0.0719	-0.806
	(0.278)	(1.602)	(0.285)	(0.749)
Constant	5.596***	7.283***	1.392**	-0.489
	(0.628)	(2.323)	(0.534)	(1.087)
Effect of caste conditional on social connectedness:				
L type (α_1)	0.445*	0.004	-0.403*	0.650
	(0.247)	(1.260)	(0.222)	(0.589)
M type (α_1+ α_1)	0.151	-0.268	-0.474**	-0.156
	(0.160)	(0.724)	(0.230)	(0.339)
H type (α_1+ α_4)	-0.123	2.120**	-0.446*	-1.154**
	(0.355)	(1.022)	(0.246)	(0.478)
Number of observations	268	67	268	67
Number of sessions	67	67	67	67
R^2	0.109	0.231	0.087	0.195

Note: Controls include age, dummy for Hindu, primary schooling complete, native state is Bihar, and currently employed. Standard errors clustered at session level in parenthesis, except when the unit of analysis is the group. Significant at *10%, **5% and ***1%.

Table 3A.6: Impact of group composition on coordination by incentive (conditional estimates)

	Excess Individual Output	**Within-Group Output Dispersion**
	(1)	(2)
Socially Connected (β_1)	-0.275	-0.359*
	(0.319)	(0.265)
Bonus (Gain Framing) (β_2)	0.201	-0.041
	(0.253)	(0.179)
Bonus x Socially Connected (β_3)	-0.239	0.043
	(0.338)	(0.298)
Constant	1.355**	0.747**
	(0.515)	(0.901)
Number of observations	268	67
Number of sessions	67	67
R^2	0.089	0.132

Note: as elucidated in Table 4.7 above.

Table 3A.7: Impact of group composition on output by incentive (conditional estimates)

	Individual Output	Group Output
	(1)	(2)
Socially Connected (β_1)	0.553	1.123**
	(0.333)	(0.555)
Bonus (Gain Framing) (β_2)	-0.004	-0.361
	(0.322)	(0.421)
Bonus (Gain Framing) x Socially Connected (β_3)	-0.335	0.458
	(0.409)	(0.675)
Bonus (Loss Framing) (β_4)	0.360	0.154
	(0.318)	(0.421)
Bonus (Loss Framing) x Socially Connected (β_5)	-0.822**	-0.991
	(0.404)	(0.681)
Constant	5.522***	6.357***
	(0.592)	(1.902)
Number of observations	268	67
Number of sessions	67	67
R^2	0.127	0.242

Note: as elucidated in Table 4.6 above.

Figure 3A.1: Recruitment advertisement

Figure 3A.2: A finished bracelet

3.B Theoretical Framework

Claim 3.B.1. *Assume that* $\bar{\theta}\underline{e} \geq \underline{\theta}\bar{e}$*, and that parameter values satisfy:* $\min(\frac{D\bar{\theta}}{2\alpha^U}, \frac{D\underline{\theta}}{\alpha^C}) \geq c > \frac{D\underline{\theta}}{\alpha^U}$.[43] *Then we have the following risk dominant equilibria in the connected game:* $\bar{e}, \bar{e}$ *in the homogeneous types case, and high effort for the low ability worker with low effort for the high ability worker in the heterogeneous abilities case. In the unconnected game we have the following risk dominant equilibria:* $\bar{e}, \bar{e}$ *in the high ability homogeneous types case,* $\underline{e}, \underline{e}$ *in the low ability homogeneous types case as well as in the heterogeneous abilities case. Moreover, conditional on the higher output in the connected game (i.e homogeneous low ability case, and heterogeneous ability case), coordination is also higher in the connected game, if* α^C *is sufficiently smaller than* α^U.[44]

Proof of Claim 3.B.1

Proof. We use two lemmas to prove Claim 3.B.1

First we show the equilibria in the homogeneous ability game in the following lemma:

Lemma 3.B.1. *(1) Let* $k \in \{C, U\}$*. Assume that* $\frac{D\theta}{\alpha^k} \geq c$ *(or* $\frac{D\theta}{c} \geq \alpha^k$*). There are two pure strategy equilibria -* $(\bar{e}, \bar{e})$ *and* $(\underline{e}, \underline{e})$*. Worker i prefers to play* $\bar{e}$ *iff the opponent has a probability* $p_j \geq \underline{p}^k = \frac{\alpha^k c}{D\theta}$ *of playing* $\bar{e}$*. If* $c < \frac{D\theta}{2\alpha^k}$*, then the high effort equilibrium is risk dominant. Moreover as the piece rate, D, increases the probability of playing the high effort equilibrium increases. (2) Assume that* $\frac{D\theta}{\alpha^k} < c$ *then, there is a unique low effort equilibrium in this game.*

Proof. (1) It is easy to see from the game that there are two pure strategy equilibria. Worker i strictly prefers to play $\bar{e}$ iff

$$D\theta(p_j\bar{e} + (1-p_j)\underline{e}) - c(p_j\bar{e} + (1-p_j)(\alpha^k\bar{e} + (1-\alpha^k)\underline{e}) \geq D\theta\underline{e} - c(p_j(\alpha^k\underline{e} + (1-\alpha^k)\bar{e}) + (1-p_j)\underline{e})$$

[43] These restrictions are equivalent to $\alpha^U > \frac{D\underline{\theta}}{c} \geq \alpha^C$ and $\alpha^U \leq \frac{D\bar{\theta}}{2c}$, used in the main text.

[44] Most of the results of Claim 3.B.1 do not depend on the restrictions on parameters. The assumption that $\bar{\theta}\underline{e} \geq \underline{\theta}\bar{e}$, is not necessary for our results. Indeed, connected groups are always more likely to converge to the higher group output equilibrium since $\underline{p}^C < \underline{p}^U$, (which is driven by $\alpha^C < \alpha^U$). Moreover the result that individual effort need not be significantly different depends on the parameter restrictions – the parameters have been chosen to ensure that unconnected groups can coordinate on the high effort equilibrium in the high ability case. However as long as the difference, $\bar{\theta} - \underline{\theta}$ is sufficiently high, the result holds even without these restrictions. Lemmas 3.B.1 and 3.B.2 provide a characterization of the pure strategy equilibria for all parameter values.

This is true iff $p_j \geq \underline{p}^k = \frac{c\alpha^k}{D\theta}$. Risk dominance requires $\underline{p}^k < \frac{1}{2}$ and this is the case iff $\frac{c\alpha^k}{D\theta} < \frac{1}{2}$, or $c < \frac{D\theta}{2\alpha^k}$. $\frac{\partial \underline{p}^k}{\partial D} = -\underline{p}^k \frac{1}{\theta D}$, so as piece rates increase, $\underline{p}^k$ decreases. (2) The high effort equilibrium exists iff $p_j = 1 \geq \underline{p}_k$ i.e. $D\theta \geq c\alpha^k$. The low effort equilibrium exists if $p_j = 0$ – in this case low effort is always a best response.

□

Second we now show the equilibria in the heterogeneous ability (one high and one low ability worker) game in the following lemma where we assume that $\bar{\theta}\underline{e} \geq \underline{\theta}\bar{e}$, i.e $\frac{\bar{\theta}}{\underline{\theta}} \geq \frac{\bar{e}}{\underline{e}}$.

Lemma 3.B.2. *Assume that $\bar{\theta}\underline{e} \geq \underline{\theta}\bar{e}$, and $\frac{D\theta}{\alpha^k} \geq c$. There is a unique pure strategy equilibrium where the high ability worker plays $\underline{e}$ and the low ability worker plays $\bar{e}$.*

Proof. If the high ability worker puts in high effort she gets $D\underline{\theta}(p_j\bar{e} + (1-p_j)\underline{e}) - c(p_j\bar{e} + (1-p_j)(\alpha^k\bar{e} + (1-\alpha^k)\underline{e})$ while if she puts in low effort she gets $D\underline{\theta}(p_j\bar{e} + (1-p_j)\underline{e}) - c(p_j(\alpha^k\underline{e} + (1-\alpha^k)\bar{e}) + (1-p_j)\underline{e})$. Clearly low effort is better for any p_j, hence $\underline{p}_B \geq 1$ (low effort is a strictly dominant strategy). If the low ability worker puts in high effort she gets $D\underline{\theta}\bar{e} - c(p_j\bar{e} + (1-p_j)(\alpha^k\bar{e} + (1-\alpha^k)\underline{e}))$ while if she puts in low effort she gets $D\underline{\theta}\underline{e} - c(p_j(\alpha^k\underline{e} + (1-\alpha^k)\bar{e}) + (1-p_j)\underline{e})$. This holds for any $p_j \geq 0$, as long as $\frac{D\theta}{\alpha^k} \geq c$. Hence $\underline{p}_S = 0$, i.e. high effort is a strictly dominant strategy for the low type. □

Table 3B.1 below illustrates the equilibria derived from Lemmas 3.B.1 and 3.B.2 when $\alpha \in \{\alpha^C, \alpha^U\}$.

Table 3B.1: Risk dominant equilibria (homogenous game) assuming $\frac{D\overline{\theta}}{2} > D\underline{\theta}$

	$\frac{D\underline{\theta}}{2\alpha} \geq c \geq 0$	$\frac{D\underline{\theta}}{\alpha} \geq c > \frac{D\underline{\theta}}{2\alpha}$	$\frac{D\overline{\theta}}{2\alpha} \geq c > \frac{D\underline{\theta}}{\alpha}$	$c > \frac{D\overline{\theta}}{2\alpha}$
$\underline{\theta}, \overline{\theta}$	$\overline{e}, \underline{e}$	$\overline{e}, \underline{e}$	$\underline{e}, \underline{e}$	$\underline{e}, \underline{e}$
$\overline{\theta}, \overline{\theta}$	$\overline{e}, \overline{e}$	$\overline{e}, \overline{e}$	$\overline{e}, \overline{e}$	$\underline{e}, \underline{e}$
$\underline{\theta}, \underline{\theta}$	$\overline{e}, \overline{e}$	$\underline{e}, \underline{e}$	$\underline{e}, \underline{e}$	$\underline{e}, \underline{e}$

Claim 3.B.1 follows from the following table which compares the equilibria (connected vs unconnected) for each combination of types when the parameters are re-

stricted to $\min(\frac{D\bar{\theta}}{2\alpha^U}, \frac{D\underline{\theta}}{\alpha^C}) \geq c > \frac{D\underline{\theta}}{\alpha^U}$.[45]

Table 3B.2: Comparison of selected equilibrium in Connected vs Unconnected game

	$\frac{D\underline{\theta}}{\alpha^U} \geq c$	$\min(\frac{D\overline{\theta}}{2\alpha^U}, \frac{D\underline{\theta}}{2\alpha^C}) \geq c \geq \frac{D\underline{\theta}}{\alpha^U}$
$\underline{\theta}, \overline{\theta}$	$\overline{e}, \underline{e}$ vs $\overline{e}, \underline{e}$	$\overline{e}, \underline{e}$ vs $\underline{e}, \underline{e}$
$\overline{\theta}, \overline{\theta}$	$\overline{e}, \overline{e}$ vs $\overline{e}, \overline{e}$	$\overline{e}, \overline{e}$ vs $\overline{e}, \overline{e}$
$\underline{\theta}, \underline{\theta}$	$\overline{e}, \overline{e}$ vs $\overline{e}, \overline{e}$	$\overline{e}, \overline{e}$ vs $\underline{e}, \underline{e}$

Based on the comparison in Table 3.1, we can see that in the second column, group output in the connected game is larger than in the unconnected game, wasted effort is smaller (when types are heterogeneous, then wasted output in the connected game is $\bar{\theta}\underline{e} - \underline{\theta}\bar{e}$ which is smaller than wasted effort in the unconnected game, $\bar{\theta}\underline{e} - \underline{\theta}\underline{e}$) and individual output is higher but by less than group output. We show the computations below.

Recall that each combination of types is equally likely by assumption. Therefore we can compute the average group output, average individual output and average wasted effort and compare the difference for connected vs unconnected groups. In the connected game group output is $\frac{1}{4}\bar{\theta}\bar{e} + \frac{3}{4}\underline{\theta}\bar{e}$, while in the unconnected game it is $\frac{1}{4}\bar{\theta}\bar{e} + \frac{3}{4}\underline{\theta}\underline{e}$. The difference in group output for connected vs unconnected groups is therefore $\frac{3}{4}\underline{\theta}(\bar{e} - \underline{e})$. Coming to the individual output, note that there is no difference in the output of the high ability individual between connected and unconnected groups. However the difference is in the output of the low ability individual: $\underline{\theta}\bar{e}$ in the connected case and $\underline{\theta}\underline{e}$ in the unconnected case. The average worker output difference between connected vs unconnected is therefore $\frac{1}{4}\underline{\theta}(\bar{e} - \underline{e})$, which is smaller than the difference in group output.

Moving to the expected wasted output in the heterogeneous game, the connected game has average wasted output of $\frac{1}{2}(\bar{\theta}\underline{e} - \underline{\theta}\bar{e}.)$ In the unconnected game average wasted output is $\frac{1}{2}(\bar{\theta} - \underline{\theta})\underline{e}$. The difference in average wasted effort in connected vs uncon-

[45]These restrictions are equivalent to $\alpha^U > \frac{D\underline{\theta}}{c} \geq \alpha^C$ and $\alpha^U \leq \frac{D\bar{\theta}}{2c}$, used in the main text.

nected groups is therefore $\frac{1}{2}\left(\bar{\theta}\underline{e} - \underline{\theta}\bar{e} - (\bar{\theta} - \underline{\theta})\underline{e}\right) = -\frac{1}{2}\underline{\theta}(\bar{e} - \underline{e})$.

Note, however, that we have another measure of coordination when the games are homogeneous, i.e. $\underline{p}$. Claim 3.B.1 shows that conditional on higher output in the connected homogeneous game, $\underline{p}^C < \underline{p}^U$ for the high effort equilibrium. Thus wasted effort should be lower even off equilibrium in the high ability homogeneous connected game relative to the high ability homogeneous unconnected game. In the low ability homogeneous game, the coordination on low effort equilibrium is higher, the higher is $\underline{p}$. Therefore coordination is higher in the low ability homogeneous connected vs unconnected game if $\underline{p}^C < 1 - \underline{p}^U$. This holds iff $\frac{c\alpha^C}{D\underline{\theta}} < 1 - \frac{c\alpha^U}{D\underline{\theta}}$, or $\frac{c\alpha^C}{D\underline{\theta}} < \frac{D\underline{\theta} - c\alpha^U}{D\underline{\theta}}$, or if $\alpha^C + \alpha^U < \frac{D\underline{\theta}}{c}$. □

Extensions

Extending the result to many players and a continuum of effort levels is more complicated. However, it is well known that the risk dominant equilibrium in a 2X2 game coincides with the one that maximizes the "potential" of the game (Young (1993)). Anderson and Holt (2001) generalised the concept of risk dominance for games with more than 2 players and more than two effort (but finite) levels. They use the idea of potential games adapted to the minimum effort game (Monderer and Shapley (1996)), but add some noise in players' behaviour. They show that the resulting refinement of Nash equilibrium - the "logit equilibrium" for the minimum effort game is unique and symmetric and maximizes the stochastic potential of a game. Chen and Chen (2011) further adapt the concept of a stochastic potential game to study a minimum effort game where players can be "in group", "neutral" or "outgroup". The adapted minimum effort game with a continuum of effort levels and $n > 1$ players is a potential game according to the Monderer and Shapley (1996) definition and has the potential function shown in equation (5) of Chen and Chen (2011) and reproduced below. Let

$e_j \geq 0$ denote worker j's effort in the group:

$$P(e_1, e_2, ..., e_n) = D\min(e_1, e_2, ..., e_n) - \frac{c}{a}\sum_{1}^{n} \alpha e_i \tag{3.3}$$

where $\alpha < 1$ denotes the level of selfishness in the group according to Chen and Chen (2011). They assume that the in-group has a lower α than the neutral group which has a lower α than the outgroup. $D > 0$ represents any incentive payments as before. We can use the unique potential maximizing equilibrium as our prediction for the case of many effort levels, our predictions would be the same as Chen and Chen (2011). Our Claim 3.B.1 then follows from Chen and Chen (2011).

3.C Women only and mixed-gender sessions

In our study we also conducted 64 women only sessions (30 Socially Connected and 34 Socially Unconnected). The experiment design for the women only sessions was very similar to what is described in the Experimental Design section except the priming. In India's patriarchal society women are typically referred to using a generic last name of *Devi* or *Kumari* (i.e. lady or girl) which would not signify their *jati* to other group members. Since caste is determined by birth and inter-caste marriages are virtually non-existent even today, in all female sessions after we announced a woman's first and generic last name we also mentioned the first and last name of the man whose wife or daughter she was, followed by her residential address. Thus, in all sessions the main experimenter followed a prepared script and said the following: "Now I will announce your name and your residential address. As I call out your names please raise your hand. If there is any error in the announcement, please tell us." In all the male (female) sessions the main experimenter announced the following: "NAME (wife/daughter of FIRST NAME, LAST NAME) and resident of...".

Table 3C.1, corresponding to Table 3.6 and Table 3.7 in the main text, reports the results for women only sessions. We do not find any significant effects of social connections on women's output or coordination. Our priming for women is indirect (it is through announcing her husband's or father's name) and hence may not be salient enough to activate her social connection. This may have been confounded by safety concerns and restricted physical mobility of women in India, due to which most women came to the sessions accompanied by other women they knew. Hence the probability of knowing someone even in the socially unconnected group was high for women. Finally, women produced significantly higher output than men in our experiment task - creating a "ceiling" effect.

We also conducted an additional experiment of 30 *mixed-gender sessions* (15 sessions for Socially Connected and 15 for Socially Unconnected) under *piece rate* in March 2017 with different subjects from the same population. Each mixed-gender session consisted of 2 men and 2 women. When we pool the observations of women in this additional experiment with the data from the 14 *all-women* sessions with Piece Rate in the main experiment we find that in the Socially Unconnected treatment, men's individual output is marginally higher in the mixed-gender groups than in the all-men groups. This difference in men's performance between the mixed-gender and the all-men groups, however, disappears in the Socially Connected treatment. Wilcoxon rank-sum tests for the group-level outcomes between the pure and mixed-gender sessions for men and women separately are consistent with the individual-level results discussed in Tables 6 and 7 in the main text. Due to restrictions on women's mobility in India, it's logistically challenging to conduct gender mixed sessions. So while our results for the mixed-gender sessions may be underpowered due to the small sample size the results are qualitatively consistent with the pure gender sessions.

Table 3C.1: Impact of group composition on output (unconditional estimates)

	Women's Output		**Women's Coordination**	
	Individual Output	Group Output	Excess Individual Effort	Within-Group Output Dispersion
	(1)	(2)	(3)	(4)
Socially Connected (α_1)	0.054	0.034	0.235	-0.048
	(0.159)	(0.348)	(0.236)	(0.172)
Bonus Incentive (α_2)	-0.121	-0.211	0.194	-0.045
	(0.173)	(0.397)	(0.294)	(0.196)
Constant	6.898***	7.598***	0.195	0.410
	(0.448)	(1.804)	(0.582)	(0.893)
Mean for Socially Unconnected	5.162	3.912	1.250	1.132
Number of observations	256	64	256	64
Number of sessions	64	64	64	64
R^2	0.114	0.210	0.084	0.129

Note: In columns 1 and 3, the dependent variable is *individual* output (number of completed wires made by a subject) and excess *individual* output (number of completed wires made by subject less the number of bracelets made by the group). In columns 2 and 4, the dependent variable is *group* output defined as the number of bracelets (i.e., the minimum number of completed wires) and the dispersion in the number of completed wires made by subjects in a group. 'Bonus Incentive' is a dummy that equals 1if the bonus was offered to the group and 0 if the incentive was piece rate. Other control variables include age, Hindu, dummy for H type, dummy for M type, and dummies for primary schooling complete, native state Bihar and currently employed. The estimates are robust to additional controls reported in Table 3A.3,Table 3A.4. Standard errors clustered at the session level are reported in parentheses (except in columns 2 and 4 where the unit of analysis is the group). Significant at *10%, **5%, and ***1%.

Chapter 4

Workplace ties: A Case Study of Women in Garment Manufacturing in India

4.1 Introduction

A well established stylized fact in labor economics is that informal channels, such as social contacts or workplace ties, are a significant resource for job search for workers (Calvó-Armengol and Jackson (2007)). Indeed, jobs obtained through referrals vary from 50% to 87% in developed countries (Topa (2011)) and 44% to 70% in developing countries (Munshi and Rosenzweig (2006)). In addition, firms often rely on employee referrals for hiring and promoting workers because of their potential to minimize moral hazard and lower search costs (see Afridi et al. (2015a) for a brief review of the literature).[1] It is not surprising, therefore, that individual's ties are often referred to as social capital (Fernandez et al. (2000), Baldassarri (2015)).[2]

However, implications of these ties on labor market outcomes vary drastically

[1]This chapter deviates from the impact of workplace ties or interactions on other outcomes such as productivity, effort and earnings

[2]I use the terms 'tie' and 'connection' interchangeably in this study.

across different demographic groups and contexts, and thus warrant deeper inspection (Ioannides and Loury (2004), Calvó-Armengol and Jackson (2004), Calvó-Armengol and Jackson (2007), Afridi et al. (2015a)). Multiple mechanisms may produce these differences, discussed briefly in subsection 4.1.2. The key understanding from this literature is that one must examine the structure, patterns, motives and expectations of individuals' ties within their micro context, in order to avoid over-generalization.[3]

To a great extent, an individual's context dictates the opportunities for establishing ties (Blau (1977)). The workplace provides opportunities (as well as constraints) for establishing ties that entail 'expressive' and 'instrumental' benefits (Ibarra (1992)).[4] Given the 'workplace context', an individual develops and maintains ties according to the purpose sought (Ibarra (1993), Wellman (1985)). Taking a cue from workplace ties literature, this study examines 'personal ties' of individuals within the context of their role as garment manufacturing workers.[5]

Most of our understanding of workplace ties come from white-collar job settings in developed countries. These studies highlight the disadvantages faced by women because they get excluded or may exclude themselves from influential ties that are instrumental in one's career growth. This exclusion is associated with loss of valuable information, referrals, and perhaps the glass ceiling effect for women in organizations (see Brass (1985) for a brief review of this literature).

Women dominate blue-collar jobs in the garment manufacturing sector across developing countries. However, they are highly underrepresented at managerial levels (Naeem and Woodruff (2014), ILO (2017)). Similar trends prevail in India (Ranganathan and Shivarama (2020)). The most popular strategy with garment factories to hire supervisors is in-house promotion policy where recommendations from current

[3]The role of ties as social capital has gained a lot of popularity across sociology, economics and political science based on the generic notion that they affect outcomes positively. However, micro econometric evidence shows that this may not always be the case (Baldassarri (2015)).

[4]'Expressive' benefits involve emotional, social support, higher closeness levels, and trust compared to ties that are exclusively for instrumental benefits (Moore (1990)). 'Instrumental' benefits involve access to resources (such as influence and information) that aid in career advancement (Ibarra (1997)).

[5]Personal ties are the set of direct relationships of an individual with others (Ibarra (1992)). Workplace ties may also contain personal ties that originated in some other settings along with ties that arise purely due to working together in a team.

line supervisors are given due weightage.[6] Thus, having personal ties or "informal interactions" with supervisors can prove instrumental for one's career.[7] Absence of informal interactions is often associated with barriers to one's career growth (Ibarra (1992)). The central theme of this paper is to examine personal ties of workers (who are most likely to be females) at the workplace with a focus on "informal interactions" with supervisors (who are most likely to be males). Moreover, Indian women face strict cultural barriers regarding mobility and cross-gender interactions (Anukriti et al. (2020), Jayachandaran (2019)) that may perpetuate the existing power dynamics.[8] Therefore, it is of practical importance to examine whether the structure of ties differs by a worker's gender, within similar workplace context.

4.1.1 Main results

Taking a worker *'i'* as the focal point, this study looks at personal ties (proxied by friendships) of 1744 blue-collar workers in two garment factories in the National Capital Region (NCR) of Delhi. These 1744 workers report in total 3060 ties (one-directional friendships). Cross-gender friendships are negligible, indicating strict gender homophily in friendships at workplace. 17% of workers do not report any friendships. The average number of friendships is around two. Even though women have a higher proportion of same-gender options available to them (85% of workers are women), they report significantly lower total number of friends (personal network size) and new friendships than men. Women have more homogeneous ties and are more likely to form friendships with workers from their regular line and same job rank (i.e., same functional group).[9]

[6] As per the interviews conducted by the author with Human Resource Managers of different factories across India under IWWAGE Early-Career Research Fellowship – Award Year 2019. Using data from Bangladeshi factory, Heath (2018) show that 44% of supervisors had acted as a referee, albeit at worker level hiring.

[7] "Informal interactions" are non-task related communication, i.e., issues that do not come directly under the purview of the supervisor.

[8] One must note that women working in factories might have already overcome mobility restrictions (to some extent) that inhibit Indian women from going out and working. Thus, this is a selective sample of Indian women.

[9] On the basis of position in the workplace hierarchy, workplace ties literature distinguishes between horizontal (with employees of same designation-ranks) and vertical ties (with employees of higher

Only 0.56% of 3060 friendships are with supervisors indicating that supervisors are outside the personal ties of workers irrespective of the gender. However, there are significant gender differences in informal interaction patterns (termed as vertical ties (Ibarra (1993))). Women are less likely to know their regular supervisor by name or reach out to them for emotional support. However, there are no gender differences in communication regarding non-personal non-task related issues.

Workers were asked the purposes for which they approached or could approach mentioned friends. Data show that while there are no gender differences in using these friendships for companionship, there are differences in expectations regarding mobilization in the future. Women are less likely to extend monetary help to their friends, take up career advice or approach supervisors for monetary help. Additionally, other interpersonal characteristics like marital status, education, native state, age, experience, etc. and workplace context variables like designation, the proportion of females in a line, etc. are not correlated with a worker's network structure.

The tie structures and interaction patterns exhibited by the women in this study are associated with a limited flow of non-redundant information and influence. Workplace ties studies from developed countries have shown that individuals who establish weak ties with high-status individuals, non-kins, and whose interactions extend beyond their immediate work group tend to gain professionally from ties (Lin et al. (1981), Moore (1990)). This *suggests* that women might not be able to take advantage of weak ties availability at the factory.

There can be several explanations for these observed gender differences in social ties. Although pinning down the exact channel is beyond the scope of this study, I briefly discuss a few possible (but not exhaustive) factors that can give rise to these patterns in section 4.6. I want to emphasize that this study is descriptive and exploratory. The impact of differences in the pattern of ties on outcomes such as upward mobility within a firm or career advancement across organizations are questions left for future studies. However, to the best of my knowledge, this study is the first to look at the

designation-ranks). Having vertical ties is considered as the key to career advancement (Ibarra (1993)).

gender differences in workplace ties in developing country. It has the potential to contribute to the re-examination of organizational behavior. Although this study covers garment manufacturing factories, it can serve as a starting point for understanding labor-intensive sectors where a particular socio-demographic group dominates managerial positions, and ties are an important source of information and influence. This study also advocates the need to examine broader contextual constraints (such as cultural barriers) that are specific (or more severe) to women.

4.1.2 Related Literature

Workplace ties and gender : stylized facts from developed countries

One of the most stylized facts from workplace management and organization literature is that men have more extensive ties than women with powerful individuals in their organizations (Miller (1986)). In addition, there is strong gender homophily at workplace and networks are segregated by gender (Brass (1985), Ibarra (1992), McPherson and Smith-Lovin (1987)).[10] Homophily and status of ties tend to be positively correlated for men and negatively for women (Ibarra (1992)). Women interact with men for instrumental benefits and establish ties with other women for expressive benefits. Additionally, ties with women are perceived to be less influential. Men tend to reap greater benefits from similar individual and positional connections, as well as from homophilous ties, relative to women (Ibarra (1992), Steven and Ports (1992), Ioannides and Loury (2004)).

Two popular perspectives have emerged as explanations of these observed gender differences. 'Dispositional' perspective argues that these gender differences in ties arise due to fundamental differences in behavior, preferences, and attitude by gender (Gilligan (1982)). For instance, women are more likely to form stronger, fewer ties, and more ties with kin than men. Women's ties are more 'relational oriented' and thus, they may not interact for career advancement. On the other hand, men interact

[10]"Homophily is defined as the tendency for people to seek out or be attracted to those who are similar to themselves." (McPherson et al. (2001))

with a variety of people and have numerous weak ties that give them access to non-redundant information.[11]

By contrast, the 'structuralist' perspective attributes these differences to the structural constraints that vary by gender. Historically, not only do men dominate positions of influence at the workplace, but they also have more opportunities to establish and maintain such ties. Many studies examining gender differences in tie structures support this perspective (Brass (1985), Moore (1990), Ibarra (1992), Ibarra (1993)). They find that controlling for differences in social positions reduces gender differences in network structures to a great extent. Further, Kanter (1977), Kanter (1979) argue that women do not occupy critical positions, but rather standardized jobs, and thus have little visibility and involvement in decision making. As a result, women find it difficult to establish instrumental ties.

Granovetter (1973) highlighted the strength of weak ties in his seminal work and since then this concept has been used widely in labor economics to show (theoretically and empirically) how smaller and tighter network density (i.e. fewer and stronger ties) can lead to unfavorable labor market outcomes for women (Montgomery (1990), Ioannides and Loury (2004), Calvó-Armengol and Jackson (2004), Mortensen and Vishwanath (1994), Lalanne and Seabright (2016)), Horvath and Zhang (2018), Lindenlaub and Prummer (2020)).

Workplace ties and gender: evidence from developing countries

The use of social ties is even more pervasive in the developing world due to either market failure and/or absence of social protection. For instance, Munshi and Rosenzweig (2006) found that the use of referrals for landing jobs is quite common in India. In lab-in-the-field experiments conducted by Beaman and Magruder (2012), 45% of the experiment participants had helped a friend or relative in finding a job with their current employer in urban Kolkata (India). From Chapter 2, we note that 64% (71%) of workers (supervisors) using the informal channel for job information, came to know

[11] "Relational orientation is the degree to which individuals engage in establishing and maintaining interpersonal relationships" (Hemmert and Kin (2020)).

about their current job opening through a factory employee. To summarize, existing studies from developing countries show the importance of employee referrals and, thus, workplace ties, but evidence on their structure and implications for women is limited.

Research from other contexts does show that women face disadvantages when information flows or is accessed through ties. For example, using experimental data from Malawi, Beaman et al. (2018) shows that men refer men despite knowing qualified women (due to strong gender homophily). However, women do not refer more qualified women (due to competition) for jobs. Further, Beaman and Dillon (2018) use social ties data from villages in Mali and find that women are less likely to receive valuable information regarding agricultural technology because they are away from influential nodes in the network. In another Malawi based study on information diffusion, Yishay et al. (2020) show that woman are perceived to be less efficient in male-dominated roles even though no difference exists in the knowledge they possess.

Another critical observation from social network studies in India is that women may have an alternate use of ties that might not exist for men due to stricter cultural barriers for women. For instance, we observed in Appendix 3.C (Chapter 3), that most women subjects came to participate in experiments only if they could find other women to accompany them. Using field experiments with SEWA bank customers, Field et al. (2016) show that getting trained with a friend improved the business activities of the participants along with an increase in their household's earnings and expenditures. Women coming from the restrictive social background were more sensitive to getting trained with a friend. Anukriti et al. (2020) using a sample of around 600 women from rural areas of Jaunpur district of U.P. show that having connections outside the household alters a woman's belief about family planning (through information channel) and helps her overcome mobility restrictions (through companionship channel).

These studies point out that cultural barriers and perceptions may play an essential role in shaping the structure and objectives of ties in a manner distinct from men. Further, ties that are helpful in one context (e.g., same-gender ties providing companionship) can be a liability in other contexts (e.g., requirement of cross-gender referrals for career mobility).[12]

The takeaway message from the literature on both developed and developing countries is that there exist multiple channels that can lead to differences in the structure and pattern of workplace ties, which may further exacerbate gender inequalities. However, studies exploring this notion are at a nascent stage for developing countries. This study attempts to fill this gap by examining personal network relationships with interpersonal characteristics (dispositional perspective) within workplace-related constraints (structuralist perspective).

The remainder of the paper is organised as follows. Section 4.2 describes the context and setting of this study. Section 4.3 discusses the data set, measurement of variables, and the summary statistics. Section 4.4 presents the data analysis and results while section 4.5 shows the heterogeneity of findings. Section 4.6 discusses the results and 4.7 concludes.

4.2 Context and background

4.2.1 Women in garment manufacturing

Globally, women represent 68% of the workforce in garment manufacturing with huge inter and intra-country variations. A job in the apparel sector could be the first formal employment opportunity for many women in developing countries (ILO (2017), BSR (2017)). Using data from Bangladeshi garment factories, Heath and Mobarak (2015) show that a job in the garment manufacturing sector is associated with the bargaining power, educational outcomes, and fertility decisions of women. Despite being in the

[12]In another context, Munshi and Rosenzweig (2006) show that previously disadvantageous group (girls) were able to take advantage of fewer network ties when traditional institutes (*jati* ties) met modern institutes (English education system). The traditional occupation of the *jati* influenced boys' schooling choice in Mumbai. However, girls experienced less resistance from social networks due to their historic non-participation in the labor force. These findings further motivate the importance of the micro context in which ties are embedded, a theme followed in this study.

majority and more productive as skilled operators, women in garment manufacturing face numerous challenges such as over-representation in low-paying and low-skilled tasks, under-representation at managerial positions, wage-gaps, unsupportive norms and power dynamics (ILO (2018)).

The most common stylized fact from various studies on garment factories is that men have historically dominated supervisory positions, which are higher than the worker positions most women are relegated to (discussed in detail later), in the management hierarchy (Naeem and Woodruff (2014)). We observed in Chapter 2 that 85% of workers from our sample are female and significantly more productive than male workers (p<0.01), yet, there are no female supervisors. These establishments do not have women even in substitute, temporary supervisory roles.

In some industrial hubs of South India like Bangalore and Tirupur, women's participation in the blue-collar positions in the factory is as high as 90%. Over time these factories have started hiring females for supervisory roles, although males still dominate these positions. Currently, only 15-20% of supervisors in South Indian factories are females (Ranganathan and Shivarama (2020)). Studies are yet to address the causes of the failure of management to hire women supervisors despite the absence of any concrete evidence of them being worse performers than male supervisors in the long run (Naeem and Woodruff (2014), Ranganathan and Shivarama (2020)).

4.2.2 Importance of ties at the factory

As elaborated in subsection 2.2.2, production in garment factories takes place in lines across multiple floors. The focus of this study is on the personal ties of line workers (operators and helpers) that not only provide emotional support but act as a "system for making decisions, mobilizing resources, concealing or transmitting information, and performing other functions closely allied with work behavior and interaction" (Lincoln and Miller (1979)). They serve as a source of expressive and instrumental benefits (Ibarra (1993)).

Workers interact with their line supervisors daily and may develop relationships that involve interactions apart from task-based. Supervisors are part of staff hiring and ranked above operators and helpers. The supervisory position is the first entry-level managerial post at the factory. Hierarchically, line in-charge, floor in-charge, and production-head succeed supervisor. The factory head is the top production managerial position at the factory and deals directly with CEOs and factory owners. In the sampled factories (similar to the garment factories in the developing countries), the managerial positions are dominated by men except for some intermediary HR positions. For a worker, ties with any of these functional groups (i.e., vertical ties) entail instrumental benefits.

Discussions with the management of the sampled factories revealed no fixed time-bound promotion system. The hiring of supervisors takes place through an internal promotion process or referrals. Moreover, as discussed in Chapter 2, recommendations of existing supervisors play a significant role in screening workers for grade promotion, assistant supervisory and supervisory roles. Supervisors act as a link between workers and other managers, and thus ties with the supervisors are a primary source of instrumental benefits for the workers.

In the context of factories covered here, the importance of workplace ties is evident from the use of ties for obtaining job information for the current job of these workers. Recapitulating from Chapter 2, 75% of the blue-collar workers in stitching department had used a tie for obtaining information on the job opening at the current factory(s). 65% of these job information ties were the employees of the respective factories at the time of joining of these workers. Conditional on job information ties working at the factory (at the time of the survey), 42% of these ties also referred the respondent to the management.

Further, around 50% of these job information ties were stitching operators, followed by managers, i.e., vertical ties (29%). Conditional on the gender composition of the sample, a higher proportion of females used ties for job information (77% females, 63% males), but a higher proportion of males obtained referrals (40% females, 58% males). Also, 54% of males' job information ties were with managers, whereas this number was only 25% for females. The notable observation here is that males mobilized a higher proportion of vertical ties for instrumental benefits, even though females form the majority of the workforce in garment factories.

4.2.3 Scope of interaction at garment factories

In the sampled factories, a typical day of a worker starts at 8 am and lasts until 5 pm (excluding overtime) with a 20-minute lunch break during mid-day. There are no prescribed time slots for tea/water/restroom breaks. Moreover, the management does not have any specific policy of providing opportunities for worker interactions. Workers are usually assigned a line when they join the factory, but they can be reallocated across lines on a production floor. However, their positions are fixed within a line throughout a workday. Workers cannot choose the kind of task they perform or the lines they sit in or around whom they sit. They cannot choose the supervisors they work under either. Supervisors are designated to fixed lines by the management for a considerable period. Thus, a worker gets opportunities to interact with the same set of co-workers and line supervisors. However, one must note that within a functional group on a day, mobility restrictions and demanding nature of work put severe constraints on the workers uniformly for establishing ties during working hours.[13]

Since worker movement across floors is highly unlikely as every floor is like a small factory with lines as sub-units, a floor spans the entire set of new social contacts the worker can build. We know from Chapter 2 that the average line strength across the sample comprises 33 workers, with a range of 9 to 54 workers. Average proportion of females per line is around 80%. Thus, on any given day, the availability of same-gender contacts is significantly higher for females. The line-level functional group is the tightest and smallest network unit in the factory. Opportunities for forming new external contacts (i.e., across other floors and departments) are quite limited, but they are potential sources of new information (Ibarra (1993)).

To summarize, personal ties at the workplace are an important source of expres-

[13] A worker's functional group consists of workers from her regular line and the same hierarchy.

sive and instrumental benefits. The factory work structure puts uniform constraints on availability, proximity, and frequency of interactions for workers within similar functional unit. Given these constraints, individuals will strategically choose ties and interactions to fulfill the purposes they seek. Since there is a limit on ties that an individual can maintain, differences in the purpose itself can result in different tie structures.

4.3 Data and summary statistics

4.3.1 Data

This chapter uses data as described in section 2.3. I create cross-sectional data set on personal ties for 1744 workers by combining data from survey, production and attendance data.

Survey data

Section C and D of the questionnaire (given in Appendix I) that was administered through personal interviews as part of the census of stitching department asked workers to report their regular supervisors and co-workers whom they considered as friends. For each reported tie, a series of questions measuring the duration, frequency of interactions, communication, proximity, and mobilization followed.

4.3.2 Measurement of ties

Tichy et al. (1979) outlines an analytical framework that has formed the basis for several workplace ties based studies (e.g. Lincoln and Miller (1979), Brass (1985), Ibarra (1993), Moore (1990), Ibarra (1992), Ibarra (1997), Burt (1992)). My analysis here relies heavily on these studies for measuring the structure and interaction patterns of the ties at the sampled factories.

Personal ties

Personal ties consist of non-formal relationships that involve informal interactions (i.e., interactions not essential for accomplishing tasks in the organization). These relationships get formed due to liking and attractions (mostly arising from identity or group affiliation) when individuals work around each other (Rotemberg (1994)). We know from Chapter 2 that workers come from similar socio-economic backgrounds and residential clusters. Thus, another major source of personal ties is pre-factory relationships (older and stronger than new ties). In this study, I consider self-reported friendships with other workers employed at the factory as the set of personal ties. I use concepts of *size*, *diversity* and *range* from the network literature to measure the structure of personal ties, as follows:

Size: I take worker *'i'* as a focal point to measure each unidirectional relationship reported as one friendship (tie). This measure gives the worker's *'personal network size'* at the workplace (Moore (1990)). Further, I distinguish between friendships that form after joining the factory (i.e. *new* friendships) and pre-factory ties (i.e. *older* friendships) to gives us the size of new and older personal ties, respectively.

The sources of older friendships vary by neighborhoods, kinships, schools, training centers, previous workplace, etc. Each type of tie may be associated with different benefits. For instance, neighborhood and kinship ties can provide childcare support to mothers and thus, women may have a higher proportion of these types of ties (Moore (1990)). Whereas pure workplace ties tend to be weak (e.g. acquaintanceship), they offer new information and might be easier to maintain (Ericksen and Yancey (1977), Lin et al. (1981), Granovetter (1973)).

On the one hand, older ties are ready-made and more trustworthy (Wellman (1985)). These might also help women overcome cultural barriers. Additionally, older ties may also help to 'break the ice' at a new workplace, increasing one's personal network size. On the other hand, older ties may also have lock-in effects involving higher moral and emotional obligations (Hemmert and Kin (2020)). Thus, limited time-budget leads to a trade-off between different types of ties. An individual maintains an optimal composition depending upon the benefits offered and the costs imposed by the different types of ties (Boorman (1975)), which I capture by *diversity*.

Diversity: Diversity captures the variety in the origin of friendships at the workplace. I use three measures of diversity. First, the count of different sources of ties – *type of ties*. A higher number indicates more variety. Second, the proportion of *newer* friendships. Third, *diversity index* - share of each type of source in total friendships. The last two measures range from 0 to 1, and higher value indicates a more homogeneous structure of ties.

Range: The third measure of the structure of personal ties is the *range*, *viz.* proportion of friendships at the workplace that are outside the immediate functional group of the worker *i*. I use the count of friends (i) from non-regular lines, (ii) with different designations, and (iii) from other lines or designations (i.e. outside immediate functional group) to measure the range of ties of a worker.

Mobilization of personal ties

Ties provide a host of benefits apart from emotional support and knowledge spillovers. In fact, at times, the possibility of benefits dictates the formation of the ties. The questionnaire listed potential purposes for which workers might mobilize their friendships which are classified into two broad categories as follows.[14]

Companionship: Sum of responses from questions that emphasized providing support through company (expressive benefits) during lunch, traveling, or medical emergencies. For every affirmative answer score of 1 is assigned; 0, otherwise.

Reciprocity: I measure reciprocity by the willingness to extend monetary help to the mentioned friend. The survey asked if the worker *'i'* ever lent or can lend money (Rs. 500 and above) to the mentioned friend.[15] A score of 1 means that the worker is willing to lend money.

For each worker, I collapse data from worker-friendship level to worker level to

[14]Refer to Appendix B for the set of purposes which were finalized from the series of questions asked during the pilot of this study.

[15]INR 500 translate into ≈7.5 USD (2015), equivalent to 2-3 days earnings of these workers.

obtain mean scores. The final variables - *companionship index* ranges from 0 to 3. A score of 3 implies that the worker mobilizes all the friendships for all the aforementioned purposes; *reciprocity index* is the proportion of friends a worker can lend money to, ranging from 0 to 1. A higher value implies more use of ties for the mentioned purposes.

Vertical ties

As discussed in Section 4.2, supervisors are the most common and immediate set of vertical ties that can be most instrumental for a worker's career. Unlike other studies, I take the source of vertical tie fixed for all the workers sitting in line l and examine communication patterns between workers and supervisors through the responses given by the workers.[16] Job requirement gives both men and women similar opportunities to interact with their respective supervisors, but whether and which type of workers derive instrumental (or expressive) benefits are interesting questions to ask.

I proxy supervisor interactions by communication with the designated supervisor and knowing the supervisor by name. Communication falls into two categories - *non-task issues* and *seeks emotional support*. Non-task issues are different from routine, on-the-stitching-floor problems that a supervisor is supposed to handle.[17]

Mobilization of vertical ties

I look at the uptake of (i) *Career advice* given by supervisor and approaching him for (ii) *Monetary help* in the future. These responses measure the trust and comfort level that workers have while approaching supervisors.

[16]Workers may indeed have other sources of instrumental benefits in the factories. However, workers are least likely to select their supervisors, unlike other sources of influential ties. It is appropriate to assume that this source of tie is most readily (and exogenously) available to all workers in a line 'l'.

[17]*Non-task issues* examples - discuss salary miscalculation, security issues, lack of other facilities at the factory, and emergency leave. *Seeks emotional support* examples - discuss personal issues such as credit crunch, family disputes, landlord related issues, etc. Refer to Appendix I for the exact questions.

4.3.3 Summary statistics

Table 4.1 describes the gender differences in characteristics of 1744 workers.[18] Overall, 85% of workers are women. An average worker is 30 years of age, married Hindu from an unreserved caste category with 3.6 years of experience in the garment industry. Table 4.1, Col(4) shows that men and women differ on almost all the characteristics except attendance rate. Panel A shows that women are more likely to be older, married, belong to upper caste and less likely to have migrated from Bihar, education above secondary level, or own a mobile phone.

Panel B of Table 4.1 shows an individual's work profile related characteristics. The majority of women employees are operators (high skilled type as opposed to helpers). More than half are first-time employees and have less experience as compared to males. The average efficiency per worker is around 31%, and women are significantly more productive.

Table 4.2 summarizes the structure of personal ties (measures of dependent variable). Around 83% of the workers report at least one friendship at the workplace. A majority of these ties are new, originating at the current factory (79%). An average worker reports around two friends at the factory. Average length of friendships is around two years. In general, workers have less diverse ties that are clustered within their functional units, as evident from Panels B and C. Table 4.2, Col (4), however, shows significant gender differences in size, diversity and range of personal ties with women having fewer total and new friendships, less diverse and restricted range as compared to men. Women have significantly more older friendships and lengthier ties. t-tests show no significant differences in mobilization of personal ties.

Table 4.3 depicts interaction patterns with the regular supervisor (vertical ties) for the 1744 workers. On average, a worker has worked for nine months under the reported supervisor. Women are less likely to know their regular supervisor by name. Around 67% of workers report that they talk about non-task related issues with their supervisor with no significant difference by gender. The proportion of workers dis-

[18] Refer to Table 2A.1 for statistics on full sample

cussing personal issues (seeks emotional support) is quite low - 3.2%, with this figure being only 2.2% for women. Panel B shows the possibility of mobilization for benefits in the future. Women are less likely to consider career advice and seek monetary help. However, the overall uptake of future career advice is quite low at 2.6%. There are no significant differences in other sources of connectedness, such as caste or religion, as shown in Panel C.

In the next section, we examine whether the observed gender differences are significant when we control for variations in interpersonal characteristics and workplace constraints.

4.4 Methodology and results

4.4.1 Methodology

I use the following estimating equation to examine the effect of gender on the structure of personal and supervisor ties of stitching department workers:

$$Y_i = \beta_0 + \beta_1 Gender_i + \gamma \mathbf{X}_i + \delta \mathbf{W}_i + \epsilon_i \tag{4.1}$$

where, Y_i is the measure of *size*, *diversity* and *range* as described in section 4.2.1. $Gender_i$ takes value 1 if female, X_i is a set of variables measuring interpersonal characteristics. Interpersonal variables are individual demographic characteristics such as marital status (married=1), religion (Hindu=1), native state (Bihar=1), age, years of experience in garment manufacturing and education level along with quadratic terms for age and experience. A worker's performance is measured by her/his average efficiency for a period of 31 work days taken from Chapter 2. W_i are variables measuring workplace related constraints such as designation (operator=1), factory dummy (export factory=1), and the mean proportion of females in the line *'l'* ('Availability' of same-gender ties). 'Availability' measure comes from the panel used in Chapter 2.

β_1 is the main coefficient of interest and gives us the direction and magnitude of gender differences, after taking into account variation due to other personal characteristics.[19]

I use equation (4.1) for studying vertical ties as well. Here Y_i is the measure(s) of communication, as defined in Section 4.2.2. I add controls for months of working under the reported supervisor and mean strength of the line (instead of the 'proportion of females in the line' used in personal ties analysis).[20]

4.4.2 Results

Personal ties

Table 4.4 shows results from estimating equation (4.1) for different measures of the structure of ties. Gender differences in the size of personal network persists even after controlling for interpersonal characteristics and work-profile related variables. Col (1) and (2) show that women report significantly fewer total and new friends. Refer to col (1), Table 4A.1 for estimates from the first stage that gives the predicted probability of reporting personal network at workplace. Coefficients on diversity and range suggest that women have less diverse ties. Col (6) shows that women have more homogeneous

[19]Around 17% of workers reported no friendships making their personal network size zero. Running a probit model with the dependent variable as dummy=1 if a worker reported at least one friend, 0 otherwise; and interpersonal characteristics as controls, I find that probability of reporting a friend is insignificantly correlated with these covariates except (negatively with) H caste dummy. Wald statistics for overall test of significance is statistically significant. Thus, we cannot ignore this 17% of the sample. However, a simple procedure of censoring all dependent variables to zero for these observations will give misleading estimates in this particular setting. For example, consider dependent variable - 'Number of new friends' that takes value zero if an individual reports no new friendships and also because workplace network size is zero. This procedure treats both types of responses similarly, even though they are quite different (e.g. due to differences in trade-offs, constraints and underlying motivations for having a network *vs* no network and having new friends *vs* no new friends). Estimation of 'hazard of exclusion' (measured by inverse mill's ratio) and using that in the outcome equation to address this issue has been recommended widely in network analysis literature (Marsden and Hurlbert (1987), Winship and Mare (1992)). I use 'two-step heckman correction procedure' (Heckman (1979)) by using "*heckman*" package from STATA on equation (4.1). Caste dummies H and M are used as exclusion restriction in the selection equation (in Chapter 2, we demonstrated the exogeneity between caste and line assignment of a worker and importance of caste networks at workplace but no heterogeneity in the impact of these networks by caste). Refer to 2.5 for details.

[20]Regressions for worker-supervisor interactions use clustered standard errors at the modal line levels of the worker. I use a modal line for each worker i.e. the line in which worker sat for the maximum number of days from the productivity data used in Chapter 2. Correlation between reported line and the modal line is 0.9996, ($p < 0.01$). Since the two-step procedure does not allow clustering of standard errors, I also report results without clustered standard errors in Appendix 4.A for worker-supervisor interactions.

ties as compared to men. β_1 is negative and significant in col(7),(9) indicating that women have fewer contacts outside their immediate functional groups.

Coefficients on interpersonal variables and other work profile related variables are mostly insignificant (not reported due to space constraints). Detailed results on the interpersonal variables for *size* of personal networks, by gender, are in Table 4A.2, (col(4)-(6)) and (col(7)-(9)).[21] Similar to the overall sample, we observe that variables related to interpersonal characteristics and the workplace are not correlated with size of personal network for either gender. Observations from Table 4.4 and Table 4A.2, thus, leads us to the following conclusions:

Result 4.1: Women have smaller personal networks at the workplace as compared to men.

Result 4.2: Variations in interpersonal and workplace characteristics are insufficient for explaining the observed gender differences in personal networks.

Vertical ties

Table 4.5 shows results for worker-supervisor communication with standard errors clustered at the modal line level. Females are significantly less likely to know their supervisor by name (col (1)) and seek emotional support with the supervisor (col (7)). The coefficient on 'gender' is negative for *non-task related* communication, albeit insignificant. 'Months of working together' has a positive and significant relationship with the different interaction measures and sub-samples.[22]. We, therefore, get the following result from Table 4.5

Result 4.3: Women are less likely to have vertical ties.[23]

Note that the coefficient on worker efficiency is insignificant throughout. Addi-

[21](Col(2), (3), Table 4A.1 give details of the first stage Heckman correction procedure.)

[22]Results without clustered standard errors reported in Table 4A.3 give similar conclusions for the main coefficient of interest (β_1)

[23]Similar results if we add line fixed effects (which also serve as a proxy for supervisor fixed effects).

tionally, similar to friendship ties (Table 4.4), coefficient on interpersonal and work-profile variables are mostly insignificant. This reinforces our result 4.2.

Mobilization of ties

Table 4.6 depicts the benefits and expectations from friendships with co-workers and supervisors. Col (1) shows no gender differences when friendships are mobilized for company during lunch, travelling to work and medical emergency. However, col (2) indicates that females are less likely to extend monetary help to their friends. Also, they are less likely to consider career advice and approach their supervisor for monetary help (Col(3) and (4)). To summarize, we observe significant gender differences in workers' perceptions regarding future benefits from workplace ties.[24] Summarizing Table 4.6 we conclude:

Result 4.4: Women are less likely to leverage vertical ties.

4.5 Heterogeneity

The existing literature has shown a strong correlation between certain interpersonal characteristics like marital status, education level and work-status with individuals' network structure (Moore (1990)). Even though results from equation (4.1) show insignificant association between interpersonal characteristics and personal network patterns, I conduct the analysis by sub-samples of worker characteristics to check for heterogeneity in these associations.

I run equation (4.1) on: (i) married/unmarried, (ii) above or equal to median level education and below median, (iii) above or equal to median factory attendance rate and below, (iv) above or equal to median number of working days and below, (v) above or equal to median per worker efficiency and below. I find no heterogeneity by the aforementioned sub-samples except for marital status. The negative correlation between size and gender is driven by the non-married sub-sample, i.e., there are no differences in personal ties of married men and women, but unmarried women have

[24]Refer to Table 4A.4 for results with non-clustered standard error on expectations from supervisor.

smaller networks as compared to unmarried men (see Table 4.7). However, I do not find heterogeneity in the informal interactions with the supervisor for any of the sub-samples.

Further, as discussed earlier, around 75% of workers had mobilized their social ties to obtain job information. I check if this experience of mobilization of ties for instrumental benefits has any heterogeneous association with the overall results.[25] Analogous to Table 4.7, I report results for sub-samples by job information source in Table 4.8. Panel B shows that the negative correlation between gender and personal ties are driven by the women who did not use ties for job information.[26]

Thus, in our sample, marriage and prior successful mobilization of ties for instrumental benefits is associated with mitigation of gender differences in workplace network composition. Interestingly, marriages in India are associated with patrilocal-patrilineal shocks that significantly restrict women's benefits from social ties (Anukriti et al. (2020)). However, migration to urban industrial hubs due to marriage may weaken restrictions imposed by patrilocal-patrilineal shocks and thus necessitate further investigation.

Table 4A.6 shows gender differences in ties used for job information (Panel A) and differences in workplace ties of women who successfully used ties for job search *vs* who did not or could not (Panel B and C). Conditional on job information source still employed at the same factory, Panel A shows that women's job information sources live in close proximity (high proportion of post-migration neighbors), involve higher level

[25]Using data from Bangladeshi garment factories, Heath (2018) shows that only 14% of workers who did not receive a referral in their first job, received referral later versus 44% of workers who received referrals in their first job.

[26]I find no heterogeneity in patterns of vertical ties for the same sub-samples. However, looking at the sample by the caste of the workers gives us interesting results for 'Knows supervisor by name' and 'Discusses non-task issues'. Table 4A.5 shows that H type men and women are equally likely to interact with supervisors, whereas M type and L type exhibit these gender differences. It is a curious result because historically, women from lower caste have higher labor force participation rates, thus greater autonomy and lesser cultural restrictions (Munshi (2019)). However, it is in line with the uptake of the financial training program by women in Gujarat studied by Field et al. (2016) and the study of South Indian plantation workers by Luke and Munshi (2011), where they find that as the bargaining power of women belonging to lower castes (former slave castes) increases, their ties with ancestral community weakens (note that in our sample majority of supervisors are M type and women from M-type are lesser likely to know their supervisors by names or interact for discussing non-tasks issues). A similar analysis is not possible for personal ties as we use caste categories for satisfying exclusion restriction.

of trust (ever lent money) and are lengthier (higher average length of ties) as compared to men's. Panel B shows similar patterns in personal ties of women who used job search ties as compared to women who did not. Even though prior mobilization is positively correlated with network size, these women still maintain strong ties with higher degree of relational orientation.[27]

The findings above underline the relevance of future studies that focus more rigorously on these channels and which may provide useful insights on cultural barriers and implications of social ties on female labor force participation.

4.6 Discussion

The analysis shows consistent differences in the structure of men's and women's personal ties even after we take interpersonal variation and structural constraints into account. Result 1 is quite surprising because factories have ample homophilous ties options for women at the blue-collar level, unlike men. One of the most important observation from our data is that women have lower expectations regarding help from supervisors (the primary source of instrumental benefits).

There can be several explanations of these results. In the Indian context, one needs to look beyond structural and dispositional perspectives. Gender norms can manifest themselves in several ways and explain these patterns. For instance, various sections of Indian society (similar to many other developing countries) emphasize maintaining the “purity" of women. Any interactions with men outside the family are frowned upon (Jayachandaran (2019)). This type of social conditioning may voluntarily restrict women from useful interactions with men at the influential positions and benefit from “strength in numbers" (Jayachandaran (2019)).

Gender norms also result in lack of awareness regarding instrumental benefits of vertical ties, lack of aspirations, and different objectives or time constraints that may hinder the development of instrumental ties for women. Future studies focusing on

[27] Following Granovetter (1973) definition of tie strength as the function of “the amount of time, the emotional intensity, the intimacy (mutual confiding) and reciprocal services”.

disentangling these effects can provide useful policy recommendations that may help managements identify high potential women through in-house referral programs.

We also observed that women and men exhibit similar pattern of ties if they had mobilized ties for current job information or are married. These events might have helped women overcome cultural barriers and mitigate safety concerns through companionship or shift in aspirations. However, women's informal interactions with supervisors are quite limited, irrespective of sub-samples considered. Further exploration is required on the kind of ties that help women achieve similar professional outcomes as men.

The critical finding from all the results above is that structure of women workplace ties are opposite of those identified in the literature for career advancement. While testing the impact of these gender differences in ties on career outcomes is beyond the scope of this study, the emerging patterns *suggest* that the reliance of managements on employee referrals can be inimical to women's career mobility. Examining this further can help us understand the factors that constrain the demand for women at supervisory positions.

4.7 Conclusion

This study examines the interaction patterns of workers in garment factories. It finds significant differences in the pattern of workplace ties by gender. Women have fewer personal ties but not when the purpose of the tie is companionship. Supervisors do not figure in the personal networks of the workers, but women are less likely to approach them for help or career advice. Neither variation in interpersonal characteristics like experience, performance, education, nor workplace related variables like designation or attendance explain these gender differences.

In the context of the Indian manufacturing sector, which is dominated by males at managerial positions, one needs to examine the role of gender norms in explaining these observed differences. Further examination is required to understand whether cultural barriers restrict women workers from cross-gender interactions. However, irrespective of the causes of these gender differences in workplace ties, firms can act as 'network equalizers' by encouraging cross-gender interactions and female representation at higher managerial level.

4.8 Tables

Table 4.1: Worker characteristics

	Overall	**Female**	**Male**	**Diff**
	(1)	(2)	(3)	(4)
	1744	**1481**	**263**	**(2)-(3)**
A. Demographics				
Age (years)	29.637	30.190	26.521	**3.669*****
	(0.164)	(0.174)	(0.433)	(0.450)
Proportion married	0.756	0.795	0.540	**0.255*****
	(0.010)	(0.010)	(0.031)	(0.028)
Proportion Hindu	0.931	0.937	0.897	**0.040*****
	(0.006)	(0.006)	(0.019)	(0.017)
Prop. of migrants from Bihar	0.264	0.252	0.335	**-0.083*****
	(0.011)	(0.011)	(0.029)	(0.029)
Prop. of secondary & above educated	0.170	0.159	0.232	**-0.073*****
	(0.009)	(0.026)	(0.010)	(0.025)
Proportion H	0.468	0.488	0.361	**0.126*****
	(0.012)	(0.013)	(0.030)	(0.033)
Proportion M	0.311	0.302	0.365	**-0.063****
	(0.011)	(0.012)	(0.030)	(0.031)
Proportion L	0.220	0.211	0.274	**-0.063****
	(0.010)	(0.011)	(0.028)	(0.220)
Prop. owning mobile phones	0.698	0.664	0.890	**-0.226*****
	(0.011)	(0.012)	(0.019)	(0.30)
B. Work Profile				
Proportion of operators	0.806	0.828	0.681	**0.148*****
	(0.009)	(0.010)	(0.029)	(0.026)
Experience in garment	3.574	3.344	4.870	**-1.526*****
manufacturing (yrs)	(0.092)	(.094)	(0.283)	(0.254)
Average efficiency	0.311	0.316	0.284	**0.032****
	(0.005)	(0.005)	(0.012)	(0.013)
Attendance rate#	0.920	0.919	0.925	-0.006
	(0.002)	(0.002)	(0.005)	(0.006)
Proportion of first time employee*	0.489	0.539	0.214	**0.325*****
	(0.012)	(0.013)	(0.025)	(0.033)

Note: Col (5) is based on *t*-test for differences in mean. # Attendance rate calculated for 61 working days, missing for 0.23%, *Joining date missing for ≈2% of the analysis sample. H (Unreserved), M (OBC), L (SC/ST) are administrative caste categories as specified by Government of India under affirmative action policies. Average efficiency taken from Chapter 2. Source: Factory survey data, Aug-Oct 2015. Standard errors in parentheses. Significant at *10%, **5% and ***1%.

Table 4.2: Personal ties at the factory

	Overall	**Female**	**Male**	**Diff**
	(1)	(2)	(3)	(4)
A. Friendships per worker	**N=1744**	**N=1481**	**N=263**	**(2)-(3)**
Reported atleast one friend	0.830	0.821	0.821	0.009
	(0.009)	(0.010)	(0.024)	(0.025)
No. of friendships with co-workers	1.757	1.730	1.893	**-0.164***
	(0.034)	(0.036)	(0.094)	(0.094)
No. of new friendships	1.390	1.352	1.605	**-0.252*****
	(0.033)	(0.035)	(0.092)	(0.092)
No. of old friendships	0.364	0.377	0.289	**0.088***
	(0.019)	(0.018)	(0.047)	(0.050)
Average length of friendships (yrs.)	2.177	2.177	1.746	**0.432***
	(0.087)	(0.095)	(0.214)	(0.242)
B.Diversity				
Type of friendships	0.944	0.949	0.916	0.033
	(0.011)	(0.012)	(0.028)	(0.031)
Prop. of new friendships	0.634	0.626	0.683	**-0.057***
	(0.011)	(0.012)	(0.028)	(0.031)
Prop. of each type of friend	0.575	0.584	0.526	0.057**
	(0.009)	(0.010)	(0.023)	(0.026)
C.Range*(No. of friends)*				
Outside line	0.568	0.539	0.734	**-0.195*****
	(0.021)	(0.022)	(0.074)	(0.06)
Different designation	0.137	0.126	0.196	**-0.070*****
	(0.007)	(0.008)	(0.022)	(0.021)
Outside functional unit	0.737	0.697	0.966	**-0.269*****
	(0.024)	(0.024)	(0.078)	(0.066)
D.Mobilization				
Companionship Index	1.497	1.503	1.461	0.042
	(0.022)	(0.024)	(0.056)	(0.042)
Reciprocity Index	0.774	0.771	0.787	-0.161
	(0.771)	(0.787)	(0.774)	(0.016)

Note:Col (4) based on *t*-test for differences in mean. ≈17% of 1744 workers reported having no friendship with the co-workers. Statistics presented here are calculated after replacing no friendships with zeros. Mean differences are stronger when conditioned on reporting atleast one friend. 'Old friendships' are the ties which formed before coming to the factory such as from school, native village, kinship or neighborhood (pre-factory ties). Source: Factory survey data, Aug-Oct 2015. Standard errors in parentheses. Significant at *10%, **5% and ***1%.

Table 4.3: Vertical ties

	Overall	**Female**	**Male**	**Diff**
	(1)	(2)	(3)	(4)
A.Interactions	**N=1744**	**N=1481**	**N=263**	**(2)-(3)**
No. of months worked under	9.311	9.305	9.340	-0.035
reported supervisor	(0.363)	(0.392)	(0.970)	(1.015)
Knows supervisor by name	0.874	0.867	0.909	**-0.041***
	(0.008)	(0.009)	(0.018)	(0.022)
Discusses non-task issues	0.672	0.677	0.646	0.030
	(0.017)	(0.019)	(0.043)	(0.048)
Seeks emotional support	0.032	0.022	0.088	**-0.066*****
	(0.004)	(0.004)	(0.017)	(0.012)
B.Mobilization (in future)				
Uptake of career advice	0.026	0.020	0.065	**-0.045*****
in future	(0.004)	(0.004)	(0.015)	(0.011)
Can seek monetary help	0.402	0.355	0.665	**-0.310*****
	(0.012)	(0.012)	(0.029)	(0.032)
C. Other sources of connections	**N=1450***	**N=1234**	**216**	**(2)-(3)**
Belong to same caste (=1)	0.359	0.361	0.352	0.009
	(0.014)	(0.014)	(0.033)	(0.035)
Belong to same religion (=1)	0.657	0.650	0.699	-0.049
	(0.012)	(0.014)	(0.031)	(0.035)

Note:Col (4) based on *t*-test for differences in mean. *Conditional on knowing supervisor's name (required for mapping with supervisor database). Source: Factory survey data, Aug-Oct 2015. Standard errors in parentheses. Significant at *10%, **5% and ***1%.

Table 4.4: Personal ties at the workplace

	Size			*Diversity*			*Range*		
	No. of friends	No. of new friends	No. of old friends	Types of friendships	Prop. of new friendships	Share of each type	Outside line	Different designation	Outside functional grp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gender (β_1)	-0.354*	-0.379*	0.025	0.011	-0.057	0.074*	-0.475***	-0.081	-0.405***
(Female=1)	(0.191)	(0.198)	(0.107)	(0.053)	(0.054)	(0.042)	(0.130)	(0.084)	(0.138)
Experience(yrs)	-0.014	0.052*	-0.066***	-0.002	0.025***	0.006	0.002	0.005	-0.003
	(0.026)	(0.027)	(0.015)	(0.007)	(0.007)	(0.006)	(0.018)	(0.011)	(0.019)
Operator (=1)	0.162	-0.030	0.192***	0.049	-0.048	-0.008	0.084	-0.770***	-0.452***
	(0.106)	(0.110)	(0.059)	(0.030)	(0.030)	(0.023)	(0.072)	(0.046)	(0.076)
Worker's avg.	0.144	0.238	-0.094	0.099	0.020	0.052	0.049	0.048	0.070
efficiency	(0.248)	(0.255)	(0.139)	(0.069)	(0.070)	(0.054)	(0.169)	(0.108)	(0.178)
Prop. of females	-0.827	-0.663	-0.164	-0.004	-0.108	0.308	1.296*	-0.677	0.426
in the line	(1.129)	(1.163)	(0.629)	(0.313)	(0.317)	(0.243)	(0.765)	(0.491)	(0.809)
Constant	2.619**	2.856**	-0.237	1.003***	1.060***	0.467*	-0.458	1.338**	0.599
	(1.277)	(1.317)	(0.713)	(0.355)	(0.359)	(0.276)	(0.867)	(0.556)	(0.916)
Characteristics									
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	19.847*	28.955***	43.644***	11.750	36.495***	24.273**	61.049***	397.579***	93.325***
λ	-1.219	-1.131	-0.088	-0.307	-0.185	-0.043	-0.517	-0.256	-0.456
N	1744	1744	1744	1744	1744	1744	1744	1744	1744

Note: Dependent variable in Col(2) is count of friendships that originated at current factory; Col(3) is count of pre-factory friendships with sources ranging from childhood friends, neighborhood, native village, past co-workers, etc.; Col(4) is count of different types of sources of friendships; Col(5) is proportion of new friendships out of total friendships; Col(6)mean share of friends per tie, Col (7)-(9) is number of friendships outside regular line, with different designation and non-regular line or designation (i.e. outside functional unit), respectively. All regressions run using *heckman* package (STATA). Characteristics controls in outcome equation are married, Hindu, migrant from Bihar, age, age-sq, experience-sq, and education level. See col(1) Table 4A.1 for results on selection equation. Standard errors in parentheses. Source: Factory worker survey, Aug-Oct 2015. Significant at *10%, **5% and ***1%.

Table 4.5: **Patterns in vertical ties (interactions with supervisor)**

	Knows supervisor by name			*Discusses non-task issues*			*Seeks emotional support*		
	Overall	Female	Male	Overall	Female	Male	Overall	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gender (β_1)	**-0.369*** **			-0.034			**-0.676*** **		
(Female =1)	(0.126)			(0.065)			(0.146)		
Experience (yrs)	0.030	0.037	-0.113	0.067***	0.072***	0.009	0.069	0.036	0.214**
	(0.030)	(0.029)	(0.083)	(0.020)	(0.023)	(0.033)	(0.046)	(0.048)	(0.108)
Months worked	0.054***	0.050***	0.142**	0.011***	0.011***	0.012***	0.015***	0.012**	0.029***
with supervisor	(0.018)	(0.017)	(0.064)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)
Operator (=1)	0.223	0.144	0.872***	0.265***	0.305***	0.151	0.272	0.340	0.059
	(0.143)	(0.159)	(0.307)	(0.051)	(0.057)	(0.092)	(0.201)	(0.251)	(0.273)
Worker's avg.	-0.006	0.016	0.329	0.036	0.067	-0.040	-0.207	-0.254	-0.251
efficiency	(0.242)	(0.255)	(0.598)	(0.104)	(0.120)	(0.224)	(0.359)	(0.319)	(0.592)
Mean strength of	-0.010	-0.011	-0.000	0.006	0.007	0.000	-0.001	-0.001	-0.007
worker's line	(0.008)	(0.009)	(0.012)	(0.005)	(0.006)	(0.008)	(0.010)	(0.010)	(0.021)
Constant	0.155	-0.793	2.232	0.127	-0.149	0.560	-4.115***	-9.370***	1.467
	(0.979)	(1.178)	(2.153)	(0.389)	(0.479)	(0.490)	(1.373)	(2.365)	(2.124)
Characteristics									
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R sq	0.098	0.092	0.284				0.124	0.101	0.181
R-sq				0.171	0.177	0.206			
N	1744	1481	263	1744	1481	263	1744	1481	263

Note: Col (1)-(3)((7)-(9)) shows results for probit regression with dependent variable taking value 1 if worker knows supervisor by name (seeks emotional support), 0 otherwise. Dependent variable in Col (4)-(6) is sum of response to questions - (i) discusses different type of non-task issues (1 if yes) and (ii) asks supervisor for emergency leave directly (1 if yes). Characteristics controls include dummy for caste categories H and M, married, Hindu, migrant from Bihar, age, age-sq, experience-sq, and education level. Robust standard errors clustered at the reported line level in parentheses. See Table 4A.3 for results without clustered standard errors. Source: Factory worker survey, Aug-Oct 2015. Significant at *10%, **5% and ***1%.

Table 4.6: Mobilization of workplace ties

	Friendships		*Expectations from supervisor (vertical ties)*					
	Companionship Index	**Reciprocity Index**	**Career advice**	**Monetary help**	**Career advice**	**Monetary help**	**Career advice**	**Monetary help**
	Overall		*Overall*		*Female*		*Male*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (β_1)	0.052	-0.025*	-0.436***	-0.627***				
(Female=1)	(0.065)	(0.014)	(0.169)	(0.104)				
Months worked			0.007	0.010***	0.009**	0.009**	0.003	0.014*
with supervisor			(0.004)	(0.004)	(0.005)	(0.004)	(0.007)	(0.008)
Experience (in yrs)	-0.008	0.009	-0.115**	-0.005	-0.167**	0.011	-0.026	-0.128***
	(0.016)	(0.006)	(0.055)	(0.021)	(0.070)	(0.024)	(0.078)	(0.048)
Operator (=1)	0.065	0.032	-0.207	0.077	-0.292	0.042	-0.077	0.164
	(0.057)	(0.023)	(0.172)	(0.090)	(0.233)	(0.095)	(0.244)	(0.237)
Worker's avg.	0.345***	0.030	-0.474	0.042	-0.658*	0.004	0.020	0.338
efficiency	(0.106)	(0.034)	(0.315)	(0.181)	(0.385)	(0.182)	(0.505)	(0.370)
Prop. of females	-0.029	-0.189*						
in the line	(0.531)	(0.108)						
Mean strength of			0.003	-0.002	0.003		0.009	-0.011
worker's line			(0.011)	(0.009)	(0.013)	(0.010)	(0.015)	(0.012)
Constant	2.320***	0.930***	-0.690	0.536	-1.539	-0.120	1.023	0.933
	(0.566)	(0.184)	(1.102)	(0.778)	(1.372)	(0.867)	(0.876)	(1.396)
Characteristics								
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	61.388***	43.089***	92.436***	183.821***	38.161***	34.568***	48.707***	53.011***
N	1744	1744	1744	1744	1481	1481	263	263

Note: The dependent variable in col (1) is sum of proportion of friends who give company for lunch/travelling daily/ helped or expected to help during medical emergency (ranges from 0 to 3), col (2) is proportion of friends an individual can lend Rs. 500 and above (ranges from 0 to 1). Results from using *heckman* package (STATA) on equation (1) in col(1)-(2). Results from probit model on equation (1) in col(3)-(8). Robust standard errors clustered at the reported line level in parentheses for col(3)-(8). See Table 4A.4 for results without clustered standard errors. Characteristics controls as defined in Table 4.4 for col(1)-(2) (Table 4.5 for col(3)-(8)). Source: Factory worker survey, Aug-Oct 2015. Significant at *10%, **5% and ***1%.

Table 4.7: Personal ties at the workplace (by marital status)

	Size			*Diversity*			*Range*		
	No. of friends	No. of new friends	No. of old friends	Types of friendships	Prop. of new friendships	Share of each type	Outside line	Different designation	Outside functional grp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: SUBSAMPLE = MARRIED									
Gender (β_1)	-0.128	-0.217	0.090	0.037	-0.097	0.007	-0.272	-0.012	-0.286
(Female =1)	(0.262)	(0.292)	(0.176)	(0.076)	(0.092)	(0.067)	(0.181)	(0.117)	(0.192)
Constant	3.474**	3.410**	0.064	0.995**	0.894*	0.383	-0.394	1.354**	0.533
	(1.441)	(1.613)	(0.967)	(0.422)	(0.506)	(0.367)	(0.992)	(0.644)	(1.056)
Characteristics Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	16.725	16.404	29.727***	14.870	21.332**	14.602	22.716**	349.359***	65.442***
λ	-0.658	-1.094	0.436	-0.281	-0.375	-0.222	0.203	0.132	0.054
N	1319	1319	1319	1319	1319	1319	1319	1319	1319
B: SUBSAMPLE = NOT- MARRIED									
Gender (β_1)	**-0.539***	**-0.529****	-0.010	-0.024	-0.001	**0.149****	**-0.749****	-0.130	**-0.564****
(Female=1)	(0.286)	(0.247)	(0.109)	(0.064)	(0.054)	(0.059)	(0.349)	(0.111)	(0.274)
Constant	0.736	0.747	-0.010	0.858	0.947*	0.813	-2.485	2.156*	-0.295
	(2.867)	(2.471)	(1.080)	(0.631)	(0.531)	(0.587)	(3.500)	(1.100)	(2.752)
Characteristics Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	7.403	16.895	15.842	11.501	17.494	14.360	8.496	81.710***	13.059
λ	-1.928	-1.553	-0.376	-0.125	0.094	0.395	-2.355	-0.345	-1.851
N	425	425	425	425	425	425	425	425	425

Note: As elucidated in Table 4.4

Table 4.8: Personal ties at the workplace (by job information source)

	Size			*Diversity*			*Range*		
	No. of friends	No. of new friends	No. of old friends	Types of friendships	Prop. of new friendships	Share of each type	Outside line	Different designation	Outside functional grp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: SUBSAMPLE = USED TIES FOR JOB INFORMATION									
Gender (β_1)	-1.089	-0.762	-0.327	-0.064	0.118	0.216	-0.529	-0.010	-0.344
(Female =1)	(1.969)	(1.261)	(0.709)	(0.235)	(0.291)	(0.298)	(0.389)	(0.240)	(0.325)
Constant	-1.841	0.071	-1.912	0.642	1.744	1.425	-0.803	2.335	1.276
	(12.291)	(7.869)	(4.422)	(1.464)	(1.819)	(1.863)	(2.429)	(1.500)	(2.022)
Characteristics									
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	0.841	4.663	8.904	3.194	11.265	2.006	21.781*	192.565***	58.895***
λ	-6.765	-4.331	-2.434	-0.806	1.001	1.025	-1.337	0.825	-0.254
N	1300	1300	1300	1300	1300	1300	1300	1300	1300
B: SUBSAMPLE = CAME THROUGH FORMAL PROCESS									
Gender (β_1)	-0.273	**-0.385***	0.112	-0.003	**-0.135***	0.059	**-0.610*****	0.103	**-0.464*****
(Female =1)	(0.210)	(0.224)	(0.131)	(0.062)	(0.078)	(0.050)	(0.177)	(0.112)	(0.167)
Constant	2.964*	3.777**	-0.813	0.898**	1.602***	0.178	-1.045	1.392*	-0.389
	(1.527)	(1.626)	(0.953)	(0.453)	(0.565)	(0.367)	(1.288)	(0.811)	(1.216)
Characteristics									
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	16.124	25.061**	12.993	8.019	14.181	22.291**	28.298***	83.506***	45.870***
λ	-0.576	-0.649	0.073	-0.302	-0.443	0.060	-0.832	0.492	-0.202
N	444	444	444	444	444	444	444	444	444

As elucidated in Table 4.4

4.9 Appendices

4.A Additional Tables

Table 4A.1: Probability of reporting atleast one friend (First stage estimates)

	Reports atleast one friend		
	Overall	*Female*	*Male*
	(1)	(2)	(3)
Gender (β_1)	0.295**	0.000	0.000
(Female=1)	(0.117)		
Experience (yrs)	0.006	0.009	-0.050
	(0.025)	(0.028)	(0.068)
Operator (=1)	-0.083	-0.025	-0.227
	(0.096)	(0.107)	(0.252)
Worker's avg. efficiency	-0.273	-0.199	-0.570
	(0.185)	(0.199)	(0.524)
Prop. of females in the line	-1.844**	-1.156	-4.272**
	(0.763)	(0.892)	(1.804)
Married (=1)	-0.086	-0.106	0.048
	(0.120)	(0.138)	(0.287)
Bihar (=1)	0.028	0.028	-0.117
	(0.086)	(0.094)	(0.246)
Hindu (=1)	0.042	-0.015	0.166
	(0.147)	(0.169)	(0.324)
Education level	0.003	-0.007	0.080
	(0.041)	(0.044)	(0.124)
Experience-sq	-0.000	0.000	0.001
	(0.002)	(0.002)	(0.004)
H	-0.158	-0.150	-0.194
	(0.098)	(0.108)	(0.263)
M	-0.061	-0.089	0.142
	(0.107)	(0.117)	(0.271)
Age (in years)	-0.089*	-0.047	-0.206*
	(0.051)	(0.058)	(0.121)
Age- square	0.001	0.000	0.003
	(0.001)	(0.001)	(0.002)
Factory (=1 if export factory)	0.335	0.219	1.086*
	(0.281)	(0.328)	(0.616)
Constant	3.887***	3.039***	7.121***
	(0.877)	(1.016)	(2.177)
χ^2	19.847*	15.637	9.230
λ	-1.219	-0.279	-1.482
N	1744	1481	263

Note: As elucidated in Table 4.4. Dependent variable takes value 1 if worker reported at least one friend, 0 otherwise.

Table 4A.2: Size of personal ties

	No. of friends	No. of new friends	No. of old friends	No. of friends	No. of new friends	No. of old friends	No. of friends	No. of new friends	No. of old friends
	Overall			*Female*			*Male*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gender **($\beta 1$)**	-0.354*	-0.379*	0.025						
(Female=1)	(0.191)	(0.198)	(0.107)						
Experience (yrs)	-0.014	0.052*	-0.066***	-0.021	0.059**	-0.080***	0.054	0.016	0.037
	(0.026)	(0.027)	(0.015)	(0.026)	(0.027)	(0.016)	(0.079)	(0.076)	(0.045)
Operator (=1)	0.162	-0.030	0.192***	0.184*	0.017	0.167***	0.020	-0.215	0.234
	(0.106)	(0.110)	(0.059)	(0.101)	(0.106)	(0.063)	(0.254)	(0.240)	(0.144)
Worker's avg.	0.144	0.238	-0.094	-0.023	0.101	-0.124	0.900	0.608	0.293
efficiency	(0.248)	(0.255)	(0.139)	(0.230)	(0.242)	(0.144)	(0.637)	(0.607)	(0.363)
Prop. of females	-0.827	-0.663	-0.164	-1.246	-1.544	0.299	-1.190	-0.915	-0.275
in the line	(1.129)	(1.163)	(0.629)	(1.041)	(1.094)	(0.651)	(1.837)	(1.735)	(1.043)
Age	-0.003	-0.045	0.041	-0.050	-0.094	0.044	0.065	0.029	0.036
	(0.067)	(0.069)	(0.038)	(0.058)	(0.061)	(0.036)	(0.147)	(0.140)	(0.084)
Age-sq	0.000	0.001	-0.001	0.001	0.002*	-0.001	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Married(=1)	0.013	-0.080	0.093	0.057	-0.029	0.086	-0.196	-0.283	0.087
	(0.130)	(0.134)	(0.072)	(0.141)	(0.148)	(0.088)	(0.290)	(0.275)	(0.165)
Bihar(=1)	0.095	0.045	0.051	0.134	0.087	0.047	-0.118	-0.156	0.038
	(0.089)	(0.092)	(0.050)	(0.087)	(0.091)	(0.054)	(0.249)	(0.235)	(0.141)
Hindu (=1)	-0.169	-0.175	0.006	-0.143	-0.210	0.067	-0.282	-0.051	-0.231
	(0.152)	(0.156)	(0.085)	(0.149)	(0.156)	(0.093)	(0.358)	(0.342)	(0.205)
Education level	0.075*	0.048	0.027	0.075*	0.046	0.030	0.055	0.057	-0.002
	(0.042)	(0.043)	(0.023)	(0.042)	(0.044)	(0.026)	(0.122)	(0.115)	(0.069)
Experience-sq	-0.000	-0.004**	0.004***	0.001	-0.004**	0.004***	-0.004	-0.003	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)
Factory dummy	0.595*	0.511	0.084	0.596*	0.581*	0.016	0.720	0.737	-0.017
(=1 if exporting)	(0.309)	(0.318)	(0.171)	(0.317)	(0.333)	(0.198)	(0.598)	(0.561)	(0.338)
Constant	2.619**	2.856**	-0.237	3.104***	3.708***	-0.604	2.006	1.914	0.092
	(1.277)	(1.317)	(0.713)	(1.107)	(1.163)	(0.692)	(2.687)	(2.555)	(1.530)
N	1744	1744	1744	1481	1481	1481	263	263	263
χ^2	19.847*	28.955***	43.644 ***	15.637	18.511*	40.314***	9.230	14.766	12.167
λ	-1.219	-1.131	-0.088	-0.279	-0.052	-0.228	-1.482	-0.820	-0.662

Note: As elucidated in Table 4.4.

Table 4A.3: Vertical ties *(without clustered standard errors)*

	Knows supervisor by name			*Discusses non-task issues*			*Seeks emotional support*		
	Overall	Female	Male	Overall	Female	Male	Overall	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gender (β_1)	**-0.369****			-0.034			**-0.676*****		
(Female =1)	(0.149)			(0.051)			(0.171)		
Experience (yrs)	0.030	0.037	-0.113	0.067***	0.072***	0.009	0.069	-0.000	0.016
	(0.030)	(0.034)	(0.102)	(0.012)	(0.013)	(0.030)	(0.056)	(0.003)	(0.013)
Months worked	0.054***	0.050***	0.142**	0.011***	0.011***	0.012***	0.015***	0.001***	0.005***
with supervisor	(0.007)	(0.008)	(0.062)	(0.001)	(0.001)	(0.003)	(0.004)	(0.000)	(0.001)
Operator (=1)	0.223**	0.144	0.872***	0.265***	0.305***	0.151	0.272	0.014	0.011
	(0.104)	(0.114)	(0.325)	(0.043)	(0.048)	(0.097)	(0.187)	(0.010)	(0.041)
Worker's avg.	-0.006	0.016	0.329	0.036	0.067	-0.040	-0.207	-0.014	-0.007
efficiency	(0.216)	(0.230)	(0.775)	(0.084)	(0.091)	(0.221)	(0.355)	(0.020)	(0.094)
Mean strength of	-0.010*	-0.011*	-0.000	0.006***	0.007***	0.000	-0.001	-0.000	-0.001
worker's line	(0.006)	(0.006)	(0.020)	(0.002)	(0.002)	(0.006)	(0.010)	(0.001)	(0.003)
Characteristics									
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.155	-0.793	2.232	0.127	-0.149	0.560	-4.115***	-0.254***	0.467
	(0.828)	(0.936)	(2.432)	(0.331)	(0.383)	(0.713)	(1.468)	(0.084)	(0.303)
Pseudo R-sq	0.098	0.092	0.284				0.124		
R-sq				0.171	0.177	0.206		0.024	0.113
N	1744	1481	263	1744	1481	263	1744	1481	263

Note: As elucidated in Table 4.5.

Table 4A.4: Expectation from vertical ties *(without clustered standard errors)*

	Career advice	Monetary help	Career advice	Monetary help	Career advice	Monetary help
	Overall		*Female*		*Male*	
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (β_1)	-0.436**	-0.627***				
(Female=1)	(0.182)	(0.100)				
Months worked	0.007	0.010***	0.009	0.009***	0.003	0.014**
with supervisor	(0.005)	(0.002)	(0.006)	(0.002)	(0.010)	(0.006)
Experience (in yrs)	-0.115**	-0.005	-0.167***	0.011	-0.026	-0.128*
	(0.049)	(0.023)	(0.064)	(0.025)	(0.091)	(0.065)
Operator (=1)	-0.207	0.077	-0.292	0.042	-0.077	0.164
	(0.161)	(0.085)	(0.195)	(0.095)	(0.303)	(0.200)
Worker's avg.	-0.474	0.042	-0.658	0.004	0.020	0.338
efficiency	(0.377)	(0.165)	(0.461)	(0.178)	(0.702)	(0.463)
Mean strength of	0.003	-0.002	0.003	0.000	0.009	-0.011
worker's line	(0.009)	(0.004)	(0.011)	(0.005)	(0.020)	(0.012)
Characteristics						
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.690	0.536	-1.539	-0.120	1.023	0.933
	(1.411)	(0.648)	(1.965)	(0.750)	(2.358)	(1.480)
Pseudo R-sq	0.080	0.059	0.079	0.022	0.051	0.059
N	1744	1744	1481	1481	263	263

Note:As elucidated in col(3)-(8), Table 4.6.

Table 4A.5: Vertical ties by the caste group of workers

	Knows supervisor by name			*Discusses non-task issues*		
	H	M	L	H	M	L
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (β_1)	0.205	**-0.660*****	**-0.752****	0.070	**-0.213***	0.022
	(0.204)	(0.197)	(0.346)	(0.078)	(0.109)	(0.113)
Months worked with supervisor	0.052**	0.049*	0.089	0.010***	0.012***	0.012**
	(0.024)	(0.027)	(0.059)	(0.003)	(0.004)	(0.005)
Worker's avg. efficiency	0.278	-0.382	0.356	0.124	0.169	-0.346*
	(0.341)	(0.331)	(0.513)	(0.162)	(0.132)	(0.188)
Mean strength of worker's line	-0.028**	0.001	-0.009	0.004	0.008	0.008
	(0.012)	(0.012)	(0.011)	(0.006)	(0.006)	(0.006)
Characteristics Controls	Yes	Yes	Yes	Yes	Yes	Yes
Factory F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.352	0.703	1.167	0.081	0.250	-0.383
	(1.367)	(1.294)	(2.075)	(0.489)	(0.676)	(0.778)
R-sq				0.192	0.176	0.178
Pseudo R-sq	0.138	0.115	0.136			
N	817	543	384	817	543	384

Note: As elucidated in Table 4.5. No heterogeneous results by caste sub-samples for *'Discusses personal problems'* or *'Expectations from supervisors'*. Similar results with line fixed effects and clustered standard errors. Source: Factory survey data, Aug-Oct 2015. Standard errors in parentheses. Significant at *10%, **5% and ***1%.

Table 4A.6: Personal ties and job information source

	Overall	**Female**	**Male**	**Diff**
	(1)	(2)	(3)	(4)
A.Job information ties/ Obs	**430**	**370**	**60**	**(2)-(3)**
Post migration neighborhood ties	0.521	0.546	0.367	**0.179*****
	(0.024)	(0.026)	(0.063)	(0.069)
Referred worker to management	0.421	0.394	0.583	**-0.189****
	(0.024)	(0.025)	(0.064)	(0.068)
Tie is a supervisor	0.286	0.246	0.533	**-0.286*****
	(0.022)	(0.022)	(0.065)	(0.061)
Same designation	0.458	0.481	0.317	**0.164****
	(0.024)	(0.026)	(0.061)	(0.069)
Line worker	0.616	0.649	0.417	**0.232*****
	(0.023)	(0.025)	(0.065)	(0.067)
Ever lent money	0.201	0.216	0.100	**0.116****
	(0.019)	(0.021)	(0.039)	(0.056)
Length of ties (yrs)	7.352	7.603	5.813	**1.789***
	0.367	0.388	1.075	1.057
Obs	**Overall (1481)**	**Mobilized ties(1133)**	**Formal process(348)**	**(2)-(3)**
B. Women personal ties				
No. of friends	1.73	1.795	1.517	**0.278*****
	(0.036)	(0.042)	(0.071)	(0.085)
No. of new friends	1.352	1.418	1.138	**0.280*****
	(0.035)	(0.041)	(0.068)	(0.083)
No. of old friends	0.377	0.377	0.379	-0.002
	(0.019)	(0.022)	(0.040)	(0.045)
Companionship Index	1.503	1.545	1.367	**0.177*****
	(0.024)	(0.027)	(0.052)	(0.057)
Can extend monetary help (prop.)	0.771	0.793	0.7	**0.093*****
	(0.011)	(0.012)	(0.024)	(0.025)
Length of ties (yrs)	2.177	2.084	2.480	**-0.396***
	(0.095)	(0.109)	(0.188)	(0.223)
C. Women's expectation from vertical ties				
Uptake of career advice	0.020	0.021	0.143	-0.007
	(0.004)	(0.004)	(0.006)	(0.008)
Can borrow money	0.355	0.363	0.330	0.032
	(0.012)	(0.014)	(0.025)	(0.029)

Note: Data in panel A conditional on job informant currently employed at the factory. Data in panel B and C is for women sub-sample, women who used (did not use) their social ties for current job information shown in col(2) (col(3)). Col (4) based on *t*-test for differences in mean. Source: Factory survey data, Aug-Oct 2015. Standard errors in parentheses. Significant at *10%, **5% and ***1%.

Chapter 5

Conclusion

This thesis attempts to understand the impact of individuals' social networks on their labor market outcomes with the underlying rationale – 'socio-economic interdependence' is likely to affect workplace outcomes. We expect this because of the proven role of social contacts as valuable social capital. It is of particular importance in developing countries where individuals have to rely extensively on their social contacts for various personal and professional objectives. Literature also shows that certain demographic groups have an edge when social networks are instrumental in accessing information and influence. However, studies examining the relationship between social connections and workplace behavior in developing countries are quite limited. The existing literature on social networks in developing countries has been limited to the household/individual's choice of occupations or entry to particular sectors. This thesis takes the existing literature further by focusing at the the post recruitment behavior in the workplace settings and using more precise estimates of productivity.

To the best of my knowledge, the chapters of this thesis are among the first to study the implications of social connectedness on blue collar workers' behavior employed in large production lines requiring coordination. Further, the micro-econometric data used in this thesis is unique and innovative in itself (whether from the factory or lab-in-the-field-experiment). Using data from the Indian garment manufacturing sector, we show a positive impact of the degree of social connectedness on worker's performance. Our findings have implications both for large assembly lines with limited scope for communication and for emerging contemporary work practices such as O-Desk where work is performed in online teams and where face-to-face interactions and scope for communication is limited. Thus, this thesis contributes to the literature on worker incentives, management practices, and firm behavior when workers are complements with limited observability of peer effort and informal channels are prevalent for accessing information and influence.

Even though this thesis exploited the inter-dependence due to familiarity-of-caste and residential clusters, it highlights the importance of considering social incentives while designing financial incentives and workers' career growth prospects. Our second chapter postulates that workers' social networks can be leveraged to improve efficiency in the absence of high-powered performance-based incentives. Designing production schedules around well-connected workers who are a potential source of network benefits to other workers can augment productivity. Results from the third chapter suggest that being socially connected to co-workers significantly improves group coordination and output, though not individual productivity when individual payoff depends upon group performance. Further, we find that high powered incentives such as a lump-sum bonus may not lead to higher group productivity and coordination, regardless of social connectedness among co-workers. Thus, creating avenues for greater social interactions among co-workers at the workplace can enhance productivity and lump-sum bonus may not always give desired results. Finally, the fourth chapter examined the difference in the personal ties at the workplace that serve as a prime source of support and information. This chapter shows that women's workplace ties exhibit patterns that are opposite of those identified critical for career advancement. This study advocates the need to encourage cross-gender interactions across different hierarchies to mitigate gender inequality.

Thus, our research not only connects the laboratory literature on group coordination with the field experiments on labor productivity, it adds to the growing body of work on the relevance of personnel economics within firms to economic growth. Moreover, studying the mechanisms through which social connections lead to varied outcomes, emphasizing historically marginalized groups and cultural barriers, will have significant policy relevance. These dimensions are not only critical from inequality-in-outcomes perspective but also for analysing the implications of structural changes that developing countries are undergoing.

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Appendix I

Factory worker survey questionnaire (Chapter 2 and Chapter 4)

Worker Bio-Data Questionnaire

Operator's Information:

Name:______________________

Card Number | | | | | | |

Company's Name_____________

Factory Address ____

Surveyors Information:

Date of Survey | | | / | | | / | | | | |

Surveyor's name _________________

Surveyor's signature_______________

Thank you for taking part in this survey. We want to ask you few questions about your workplace. This survey will take your 15-20 minutes. Your answers will be kept confidential.

Section I. WORKER CHARACTERISTICS
A. Personal characteristics

1. **Full Name:** Last Name:______________________ **First Name** ______________________

2. **Gender:** (0)**Female** (1)Male

3. **Age (in years):** | | |

4. **Native Village**:___________________ **(2)** District: _____________________________

   (3)State: _____________

5. **Marital Status**: (1)Married (2) Unmarried (3)Divorced/Separated (4)Widow/er
   (9)Other _____________________

6. **Religion**: (1)Hindu (2)Muslim (3)Christian (4)Sikh (9)Others

7. **Sub Caste** :____

8. **Caste Category:** (1)SC (2)ST (3)OBC (4)General
   (999)Don't Know

9. **Current Address**:____

10. **Education Qualification:** (0)Illiterate (1)Literate but no schooling (2) Class 5 or below
(3) Class 6 to 10 (4) Class 11 to 12 (5)BA/B.Com/B.Sc. (6)M.A/M.Com/M.Sc
(7) Professional training (9) Other(specify)___________________________________

B. WORK EXPERIENCE AND TRAINING

1. Years in garment industry [ ][ ] Year [ ][ ] Month [ ][ ][ ] Days

2. Date of joining this Factory (DD/MM/YYYY): [ ][ ] / [ ][ ] / [ ][ ][ ][ ]

Please refer to the previous week and answer the following question:

3. Factory Floor Number [ ]

4. Section………………………………………………

5. If you worked in the assembly line, Assembly line number [ ][ ]

6. Which operation did you perform the most? ……………………………………………………………………………

Section II.INFORMATION ON CURRENT JOB

A. Please answer following question about how you obtained this job:

1. Did someone inform you about this job? (0)No (1)Yes **{If "NO",then proceed to Sec. B}**

2. Did that person work in this factory? (0)No (1)Yes

3. Does he/she still work in this factory? (0)No (1)Yes **{If "NO", then proceed to q.10}**

4. If "yes" for q.3 then please answer following questions about that person:

1.Name	2.Designation (Refer codes)	3.Floor Number	4. Line No.	5. How did you know this person? (Refer codes)	6. Did he refer you for this job? code: (No=0 / Yes=1)
7.Since how long have you known this person? (Year /months/ days)	**8. Have you lent him/her Rs.500 and above?** code: (No=0 /Yes=1)			**9. Can you borrow Rs.500 and above from him/her?** code: (No=0 /Yes=1)	
/ /					

Code.2. **(1)** Supervisor **(2)** Operator **(3)** Helper **(4)** Checker
(5) Assistant supervisor **(9)**Other (specify)

Code.5. **(1)** Worked with him/her before **(2)**Neighbors/lived near each other **(3)** Relative
(4) From native village/district/state **(9)** Other (specify)

{If answer is Code.5.(1), then ask q.5.a}

5.a. What was his/her designation in previous factory: **(1)** Supervisor **(2)** Operator **(3)** Helper
(4) Checker **(5)** Assistant supervisor **(9)**Other(specify)__________________________

10. How did you know this person?**(tick ✓ as many applicable):**
(1) Contractor **(2)** Have worked with him before **(3)** Neighbors/lived near each other
(4) Relatives **(5)** From native village/district/state **(6)** Training Center/Agency
(9) Other(specify)____

{If answer is (1) then ask q.10.a}; 10.a. Contractor's name___________________________

{If answer is (2) then ask q.10.b}; 10.b. What was his/her designation in the previous factory?
(1) Supervisor **(2)** Operator **(3)** Helper **(4)** Checker **(5)** Assistant supervisor
(9) Other (specify)____

B. Relations with the supervisor {**Please answer following questions about your supervisor}**

1. Name of your regular supervisor____

2. For how long have you worked with this supervisor? Years☐☐ Months☐☐Days ☐☐☐

3. Did you know this supervisor before coming to the factory? (0)No (1)Yes

{ If "NO", then ask q.5}

4. How did you know him?

(1) Worked with him/her before **(2)**Neighbors/lived near each other **(3)** Relative
(4) From native village/district/state **(9)** Other (specify)

5. Do you discuss issues related to the following with your supervisor?

Refer code: (1)Never **(2)**Sometimes **(3)**Often

(1) Facilities in the factory	☐	**(3)Security at the factory**	☐
(2) Salary related	☐	**(4) Commutation issues**	☐

6. What do you do when you have to take emergency leave?**(Tick all that applies)**
(1) Take leave without informing **(2)**Ask a colleague to inform the supervisor
(3) Informs supervisor over phone **(9)**Other(specify)

7. Do you talk to your supervisor about personnel (non-work related) problems?
{e.g: financial crunch/family related issues/health related issues}
(0)No (1)Yes **{ If "Yes",then ask (7.a)} ;** **{ If "NO", then ask q.8}**

(7.a) Has supervisor helped you on personnel (non-work related) issues? **(0)**No (1)Yes
{If "No",then ask (8)}

(7.b) How has your supervisor helped you? **(Specify all that apply)**
(1) By lending money (Rs.500 and more/Rs.500 or less (2) Informed about place to stay/policies/benefits given by government **(3)** referred or took to a doctor/advocate/mechanic etc **(9)** Other(specify)______________________________

8. Can you borrow Rs.500 or more from the supervisor? **(0)**No **(1)**Yes

9. If your supervisor leaves this factory and informs about a new opening at his/her new work place, will you join him/her?

(1) Certainly yes **(2)** Yes if pay is higher **(3)** No if pay is lower **(4)** Certainly No
(5) Depends on other factors (specify)…………………………………………… **(999)**Don't know/Can't Say

10. Did you work with **some other supervisor** during the last week? **(0)**No **(1)**Yes
{**If yes, then ask Q.(5),(6),(7) and (8) again}**

	(2) Name	(5) (Refer code)				(6) **R**efer code)

(7) (Refer code)	(7)**a** (Refer code)	(7)**b** (Refer code)	**(8)** Refer Code

C. Relations with Co-workers {Please answer some questions about your co-workers}

Can you name co-workers in the factory whom you consider your friend?

1.S.No	**2.** Name (Last/First)		**3.** Your relationship with this person **(Refer Codes)**	**4.** Person's Designation in factory **(Refer Codes)**	**5.** Factory floor No.	**6.** Line No.	**7.** How long have you known this person? **(in years & months)**	
8.(Refer codes)	**9.(Refer Codes)**	**10.(Refer Codes)**	**11.(Refer Codes)**	**11.b.(Refer Codes)**	**12.(Refer Codes)**	**12.b.(Refer Codes)**	**13.(Refer Codes)**	**13.b (Refer Code)**

Code.3.(1) Neighbors/lived near each other **(2)**Relative **(3)**Worked with him/her before **(4)**From native village/district/state **(5)**Met in factor **(9)**other(specify)

Code.4. (1) Operator **(2)** Helper **(3)** Checker **(4)** Assistant supervisor **(5)** Supervisor **(9)**Other (specify)____

8. Did you refer or inform her/him about this job at the factory? **(Yes=1/No=0)**

9. Do you commute to and fro with her/him?
(0) No **(1)** Daily **(2)** 2-3 times in a week **(3)** Sometimes **(9)** Other (specify)________________

10. Do you eat lunch with her/him during the lunch break in the factory?
(0) No **(1)** Daily **(2)** 2-3 times in a week **(3)** Sometimes **(9)** Other

(specify)______________

11. Do you call her/him on the phone? **(Yes=1/No=0)** **{If yes, ask q.11.b}**

11.b. Approximately how many times you called her/him in the last 7 days?
(1) One-two times **(2)** three-four times **(3)**four times or more (**4**)almost everyday

(9) Others(specify)__________________________

12. Have you ever asked for his/her help in case of a medical emergency with you or your family?**(Yes=1/No=0)**

{If "No", then ask 12.b}

12.b. Can you ask? **(Yes=1/No=0)**

13. Have you ever lent him/her Rs. 500 or more? **(Yes=1/No=0)** **{If "No", then ask 13.b}**

13.b. Can you lend Rs.500 or more to him /her? **(Yes=1/No=0)**

Appendix II

Experiment instruction manual (Chapter 3)

EXPERIMENT INSTRUCTION MANUAL

I. Setting of the "lab"

The lab consists of 4 work stations, numbered 1-4 from the extreme left of the room. In each work station there is a covered bowl of beads of a single color (white, red, green or blue) and a bundle of wires. Each bundle consists of 10 wires, each 20 cms. in length and with one end twisted. All wires are of the same color (or distribution of colors) across workstations. Works stations are separated by curtains.

4 workers of the same sex in each session.

Before the 4 workers enter the 'lab' they are randomly handed an ID number between 1 to 4 (in a folded piece of paper) by the experimenter at the door. The worker takes this into the lab, opens the paper and shows it to the experimenter inside the lab. The experimenter seats the worker in the assigned work station. (Note: There is a fixed mapping of IDs to bead colors: 1=red, 2=green, 3=blue, 4=white).

II. Experimental Instructions:

(Notes for experimenters: Once the workers are seated by their ID number, ask the workers to keep the ID numbers to themselves, and not to show it to others. Go over the instructions and answer questions when everyone can see everyone else (DO NOT DRAW CURTAIN UNTIL EXPERIMENT BEGINS).

General Information:

Welcome! Today you are going to be a part of an experiment which will take approximately 30 minutes of your time. From now on and till the end of the experiment you are not allowed to communicate with each other. You are requested to switch off your mobile phones. You may raise your hand whenever you have a doubt.

When you entered this room you were given a number. This is your experiment ID. Do not share this ID number with your team mates.

You will be receiving Rs. 200 for coming here as a participation fees. You can earn more by performing a simple task in the experiment. You will individually receive the entire amount at the end of the experiment.

Description of the Task

Your team will be making strings for a bracelet that will look like this (show a sample bracelet). For making strings for this bracelet a box of beads and a bundle of wires have been placed in front of you. Please pay attention to what I am about to explain. As you can see this bracelet comprises of 4 colored breaded string: red, green, blue and white. You have been given 20cm long wires which are twisted at the end. You are supposed to bead the wires fully from the non-twisted end. Wires will be counted for payment only if they are completely filled like this (show one sample). After filling up the wire, twist the upper part like this so that beads don't fall. (Demonstrate using one of the wires). You can make as many strings as you want by using the beads and wires that have been provided to you.

Each individual has been allotted beads of a different colour. You are required to be seated at the place alloted to you for the entire experiment and work with your own box of beads and wires. We will separate you all by drawing the curtains lying at your sides so that you can't see each others' beads color and output.

You will get ten minutes to do the task. In the end you will be informed about number of strings of each colour but not about the individual who made that colour strings. After leaving the experiment room you may discuss each other's output if you wish.

Payoffs

(**PIECE RATE**)

We will collect the filled wires by coming to you after your ten minutes are over while you remain seated. **Please keep in mind that you are required only to fill the wires to prepare strings and not assemble them to make a bracelet.** As you can see, for assembling wires into a braclet we need completely filled four wires, one of each colour. Every team member will recieve Rs. 100 for each bracelet. Everyone will be paid according to the team output.

(**GIVE TABLE BELOW TO EACH SUBJECT**)

No. of bracelets by team	Individual payoff (plus Rs. 200 for participation)
1	Rs. 100
2	Rs. 200
3	Rs. 300
4	Rs. 400
5	Rs. 500
6	Rs. 600
7	Rs. 700
…	…

Now, I am going to give you few examples to help you understand your team output and individual earnings: (EXPERIMENTER PLEASE PROVIDE EACH WORKER WITH A SHEET OF PAPER AND A PENCIL).

1. Suppose a team beaded 7 red, 7 green, 8 blue and 6 white coloured strings fully. Using these beaded wires we can prepare only 6 bracelets. Therefore, this team will get 100*6=Rs. 600.

2. Now suppose, in the same example, one of the green string is incomplete. Even now we can prepare 6 bracelets and therefore everyone will get 100*6=Rs. 600.

3. Continuing with the first example, now suppose, one of the white string is incomplete. In this case, only 5 bracelets can be made using strings produced by the team. Therefore, eveyone will recieve 100*5=Rs. 500

Based on these examples, I will now ask you two questions. Please write your answers on the sheet provided to you. If you haven't understood or don't understand anything then please raise your hand.

<u>Payoff Quiz</u>

(Experimenter, ask the participants to write down their answers to these questions, and then check on their answers. Explain the payoff rule again if there is confusion/misunderstanding.)

1. Suppose a team beaded 8 red, 9 green, 7 blue and 7 white strings fully. What is the team output in terms of number of bracelets and hence the individual earnings? (excluding the Rs. 200)

(Answer: 100*7=Rs. 700)

2. In the same example consider the situation wherein two blue strings are incomplete. In this case how, what is the team output in terms of number of bracelets and individual payoff? (excluding the Rs. 200)

(Answer: 100*5=Rs. 500)

[THE FOLLOWING INSTRUCTIONS REPLACED ABOVE FOR…]

(**BONUS WITH GAIN FRAMING**)

Every team member will recieve Rs. 100 for each bracelet. Everyone will be paid according to the team output.For example, if team output can prepare 1 bracelet then eveyone will recieve Rs. 100 each, or, if team output is for 5(or more) braclets then everyone will receive Rs. 150 as bonus which will be over and above Rs. 500. In such case individual earnings will be Rs. 500 for 5 bracelets plus Rs. 150 as bonus i.e. everyone in the team will earn Rs. 650....(discuss payoff table)

(**GIVE TABLE BELOW TO EACH SUBJECT**)

No. of bracelets by team	Individual payoff (plus Rs. 200 for participation)
1	Rs. 100
2	Rs. 200
3	Rs. 300
4	Rs. 400
5	Rs. 500+Rs. 150=Rs. 650
6	Rs. 600+Rs. 150 =Rs. 750
7	Rs. 700 +Rs.150 =Rs. 850
……	…..

[(AFTER discussing payoffs) Experimenter shows four tokens for Rs. 150 each which the subjects will be given if they meet the threshold to collect the bonus. <u>Don't put the tokens on their desk.</u>]

Now, I am going to give you few examples to help you understand your team output and individual earnings: (EXPERIMENTER PLEASE PROVIDE EACH WORKER WITH A SHEET OF PAPER AND A PENCIL).

1. Suppose a team beaded 7 red, 7 green, 8 blue and 6 white strings fully. Using these we can prepare only 6 bracelets and therfore, everyone in the team will receive 100*6 rupees plus 150 rupees as bonus. So, in total every individual in the team will receive Rs. 750.

2. Now suppose, in the same example, one of the green string is incomplete. In this case also, team output can prepare 6 bracelets and therefore, everyone in the team will recieve 100*6=Rs. 600 plus Rs. 150 bonus. So, in total every team member receives Rs. 750.

3. Continuing with the first example, now suppose, one of the white string is incomplete. In this case, only 5 bracelets can be made using strings produced by the team. Therefore, eveyone will recieve 100*5=Rs. 500 plus Rs. 150 as bonus. So, in total every team member receives Rs. 650.

4. Continuing with the above example, now, consider a situation in which only 4 white strings are complete. Now only 4 bracelets can be prepared and thus everyone will get Rs. 400. In this case, no one will receive the bonus.

Based on these examples, I will now ask you two questions. Please write your answers on the sheet provided to you. If you haven't understood or don't understand anything then please raise your hands.

<u>Payoff Quiz</u>

(Experimenter, ask the participants to write down their answers to these questions, and then check on their answers. Explain the payoff rule again if there is confusion/misunderstanding.)

1. Suppose a team beaded 8 red, 9 green, 7 blue and 7 white strings fully. What is the team output in terms of number of bracelets and hence the individual earnings? (excluding participation payoff of Rs. 200)

(Ans: 100*7=Rs. 700 + Rs. 150 as bonus = Rs. 850)

2. In the same example consider the situation wherein two blue strings are incomplete. In this case how, what is the team output in terms of number of bracelets and individual payoff? (excluding participation payoff of Rs. 200)

(Ans: 100*4=Rs. 400. No bonus**)**

[THE FOLLOWING INSTRUCTIONS REPLACED ABOVE FOR…]

(BONUS WITH LOSS FRAMING)

Every team member will recieve Rs. 100 for each bracelet.Everyone will be paid according to the team output and you can earn extra Rs. 150. For instance, if a team output can produce 5 complete bracelets then everyone will receive Rs. 500 plus Rs. 150 as the extra payment. But if team output is for less than 5 bracelets then the extra amount of Rs. 150 will be taken away from every individual. For instance, if team output is sufficient for making only 4 bracelets then every team member will receive Rs. 400 and the extra amount of Rs. 150 will be taken back. Or, let’s say if team output is enough for only 3 bracelets then each team member will receive Rs. 300 and the extra amount of Rs. 150 will be taken back......(discuss payoff table)

(**GIVE TABLE BELOW TO EACH SUBJECT**)

No. of bracelets by team	Individual payoff (plus Rs. 200 for participation)
7	Rs. 700+ Rs. 150 = Rs. 850
6	Rs. 600+ Rs. 150 = Rs. 750
5	Rs. 500+ Rs. 150 = Rs. 650
4	Rs. 400
3	Rs. 300
2	Rs. 200
1	Rs. 100

[(AFTER discussing payoffs) Experimenter puts four coupons with Rs. 150 in each cubicle which the subjects are asked to use for getting the extra Rs. 150.]

Now I will give you few examples to explain the calculation of the team output and individual earnings: (EXPERIMENTER PLEASE PROVIDE EACH WORKER WITH A SHEET OF PAPER AND A PENCIL).

1. Suppose a team beaded 7 red, 7 green, 8 blue and 6 white fully. Using these we can produce 6 complete bracelets. Therefore, everyone in the team will receive 100*6= Rs. 600 along with extra amount of Rs. 150. So, in total every team member receives Rs. 750.

2. Now suppose, in the same example, one of the green string is incomplete. In this case also, team output can prepare 6 bracelets and therefore, everyone in the team will recieve 100*6=Rs. 600 along with extra amount of Rs. 150. So, in total every team member receives Rs. 750.

3. Continuing with the first example, now suppose, one of the white string is incomplete. In this case, only 5 bracelets can be made using strings produced by the team. Therefore, eveyone will recieve 100*5=Rs. 500 along with extra amount of Rs. 150. So, in total every team member receives Rs. 650.

4. Continuing with the above example, now, consider a situation in which only 4 white strings are complete. Now only 4 bracelets can be prepared and thus everyone will get Rs. 400 and extra amount of Rs. 150 will be taken back.

Based on these examples, I will now ask you two questions. Please write your answers on the sheet provided to you. If you haven't understood or don't understand anything then please raise your hands.

Payoff Quiz

(Experimenter, ask the participants to write down their answers to these questions, and then check on their answers. Explain the payoff rule again if there is confusion/misunderstanding.)

1. Suppose a team beaded 8 red, 9 green, 7 blue and 7 white strings fully. What is the team output in terms of number of bracelets and hence the individual earnings? (excluding participation payoff of Rs. 200)

(Ans: 100*7=Rs. 700 + Rs. 150 extra = Rs. 850)

2. In the same example consider the situation wherein two blue strings are incomplete. In this case how, what is the team output in terms of number of bracelets and individual payoff? (excluding participation payoff of Rs. 200)

(Ans: 100*4=Rs. 400. In this case, extra amount of Rs. 150 will be taken back)

Now, I am going to announce your name and residence. Please raise your hand as your name is announced. If there is any error in the information then please get it corrected. You are not allowed to talk to each other.

(Notes for experimenters: Verify the information with each participant, and then continue onto the following instructions.)

All of you will get two minutes as practice time. Please fill only one wire for practice purpose. This string will not be counted in the final output. In case you experience any difficulty then please raise your hand without talking to each other.

We will be drawing the curtains now. You may open the boxes after you have been separated by the curtains and start practicing. (Experimenter, take away the practiced strings in an opaque manila envelope, and start the experiment by announcing the following reminder.)

You will now be given 10 minutes to string as many wires as you can to determine the final output.

You are again reminded that you will receive Rs. 200 for participation plus Rs. 100 for each complete bracelet. Your individual earnings depend upon the minimum number of one coloured strings produced by your team member.

[GAIN FRAMING: Please remember - you will receive Rs. 200 for participation plus Rs. 100 for each complete bracelet. Your individual earnings depend upon the minimum number of one coloured strings produced by your team member. If the team output is sufficient for preparing 5 or more than 5 bracelets then everyone will receive a bonus of Rs. 150 as well.]

[LOSS FRAMING: Please remember - you will receive Rs. 200 for participation plus Rs. 100 for each complete bracelet. Your individual earnings depend upon the minimum number of one coloured strings produced by your team member. If the team output is sufficient for preparing 5 or more than 5 bracelets then everyone will receive an extra amount of Rs. 150 as well, otherwise extra amount of Rs. 150 will be taken away.]

START STOPWATCH (visible to all subjects)

(When time is up, experimenter collects the strings in a big, opaque, manila envelope. Experimenter closes bead bowls and removes wires and bowls from each work station.

KEEP THE MANILA ENVELOPE IN THE ROOM ON THE TABLE VISIBLE TO ALL SUBJECTS.)

ANNOUNCE THIS PROCESS TO SUBJECTS IN THE SESSION TO ENSURE THAT THEY KNOW THEIR PERFORMANCE IS BEING KEPT PRIVATE AND IN THE ROOM.

"Please remain seated as I come to your place one by one to collect the beaded wires in this opaque envelope. It will be kept on this table."

III. Post-experiment questionnaire

Before counting the team output we request you to answer this questionnaire. Please tick the appropriate answers. In case you need any help in filling out the questionnaire then please raise your hand.
Experimenter goes over each question and checks all questions have been answered. Collects all filled up questionnaires.

EXPERIMENTER REMOVES CURTAINS

THEN the envelope is opened in front of the 4 workers and the experimenter combines them into bracelets in front of the four workers. The workers are told about the productivity of each color (so they know the minimum number of strings being made in the group and hence the payoff). However, they are NOT told who made how many.

Experimenter announces payment of Rs. X+ Rs. 200 for each worker.

[GAINS FRAMING: Workers are asked to collect their coupons for bonus payment, if applicable.]

[LOSS FRAMING: Workers are asked to return coupons or take their coupons for bonus payment, whichever is applicable.]

Payments are made to workers in an envelope. They sign receipt sheet as they go out.

Appendix III

Post-experiment questionnaire (Chapter 3)

POST-EXPERIMENT SURVEY

Date:__ __/ ____ /__ __ Session type:T1/T2/T3/T4 Session no. ☐☐

Your experiment ID ☐1 ☐2 ☐3 ☐4

1. **First name** ________________________ **Title**____________________

2. Age(in yrs) ☐☐ 3.Gender ☐0Female ☐1Male

4. Marital Status ☐1 Married ☐2 Unmarried ☐3 Divorced ☐4 Widow/er ☐9Other(specify)____________

5. Religion ☐1Hinduism ☐2 Islam ☐3 Christianity ☐4 Sikhism ☐9 Other(specify)____________

6. Are you currently employed? ☐0 No ☐1 Yes

7. If yes, then, in which among the following?
☐1Garment factory employee ☐2Other factory employee (specify) _______
☐3self employed ☐9Other (specify)______________

8. Current factory address: a. Factory name ______________________
b. Plot number _______________________
c. Colony ___________________________

9. Literacy status: ☐0Illiterate ☐1 5^{th} std or less ☐2 6^{th} to 10^{th} std
☐3 11^{th} to 12^{th} std ☐4B.A./B.Sc./B.Com.
☐5M.A./M.Sc./M.Com ☐6 Vocational Training

10. Native address: a. Village______________ b. District______________
c. State____________________________

11. Current address: a. House No.___________ b. Street No.____________
c. Colony__________________ d. City_____________________

12. Have you done beading beads into wire kind of task ever before?

☐ 0 No ☐ 1 Yes

13. Please rate today's task in terms of difficulty?

☐ 1 Very easy ☐ 2 Easy ☐ 3 Neither easy nor difficult ☐ 4 Difficult ☐ 5 Very difficult

14. Do you know any members from your team by name?

☐ 0 No ☐ 1 Yes

15. If yes, then please write their names and answer the following questions:

S.no.	a. Name	b. How do you know this person? (Tick as many as applicable)	c. In your opinion, in 10 mins, how many strings would have been completed by this person?	d. In your opinion, has this person ever done beading work?
1		☐ 1 Neighbour ☐ 2 Co-worker ☐ 3 Relative ☐ 4 Friend ☐ 5 Other______________		☐ 0 No ☐ 1 Yes ☐ 9 Don't know
2		☐ 1 Neighbour ☐ 2 Co-worker ☐ 3 Relative ☐ 4 Friend ☐ 5 Other______________		☐ 0 No ☐ 1 Yes ☐ 9 Don't know
3		☐ 1 Neighbour ☐ 2 Co-worker ☐ 3 Relative ☐ 4 Friend ☐ 5 Other______________		☐ 0 No ☐ 1 Yes ☐ 9 Don't know

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16. FOR EXPERIMENT INSTRUCTOR:

1. Is worker from our original sample? ☐ 0 No ☐ 1 Yes

2. If yes, note worker card no.
