UNIVERSITY OF CALIFORNIA
RIVERSIDE

Essays on Labor Supply and Firm Productivity in Developing Countries

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

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June 2020

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Acknowledgments

I would like to thank my advisors Anil Deolalikar and Sarojini Hirshleifer, and my committee members Joseph Cummins, Mindy Marks and Robert Kaestner for their invaluable support over the years. Through their guidance, I have learned to come up with research ideas rooted in theory and developed the scientific temper to test them using appropriate empirical methodology. In particular, I am grateful to my co-advisor Anil Deolalikar, for his unwavering belief in my research abilities. My research papers have benefitted greatly from his feedback and big-picture guidance.

I am immensely grateful to my co-advisor Sarojini Hirshleifer for taking me under her wings and training me in conducting field experiments. I would like to thank her for reading drafts of my papers and grant applications and offering her valuable insights. I wouldn't have had the confidence to undertake the difficult task of finding partner call centers and conducting a field experiment, without her continued encouragement and generosity.

I would like to thank my committee member, Joseph Cummins for being an invaluable mentor and one of my favorite teachers. Thank you for teaching me the tools to conduct empirical research, and for being kind and patient to my worthy and unworthy research ideas over the years. I would also like to thank Mindy Marks, Steven Helfand, Michael Bates and Carolyn Slone, for training me in applied microeconomics research and offering their helpful comments and suggestions on my research projects over the years. I am indebted to all my teachers and TAs at UC Riverside for being wonderful and effective instructors. I also want to thank Gary Kuzas for generally being the most helpful and nicest person in the department, especially to lost first-year graduate students.

I am extremely grateful to my mentor, Devaki Jain who encouraged me to pursue a PhD. I learned a lot about persistence and self-motivation from her. I wouldn't have been able to survive the PhD program without a foundation in economics, laid by my teachers, Badal Mukhupadhayay Soumendu Sarkar Priya Bhagowalia and Namrata Gulati at TERI University. Thank you, Badal Mukhupadhayay for checking-in on me throughout my PhD years.

I would like to express my deepest gratitude to my parents, for believing in the transformative power of higher education. They both have selflessly ensured that I have a supportive environment to thrive. An additional thanks to my mother for all the care work over the years, without which I wouldn't have been able to focus on my studies. I also want to thank my siblings, Ruhi and Rajat for always rooting for me and readily offering their help whenever I required.

A shout-out to my support group. I want to thank my old friends and study partners in Delhi, Armaan and Vani. I am immensely thankful to my dear friends, Giselle and Opinder for being my study partners in Riverside and my home away from home. I also want to thank my housemates at different points in the last six years, Giselle, Andrea, Priya, Cynthia, Stephanie and Yair for celebrating my successes and cheering me up in my failures.

I am thankful to my classmates and seniors for making the first and possibly the most brutal year of PhD better. I also want to thank all my seniors, especially Anaka, Christian, Jonny and Miro for offering their thoughts and feedback on my research. You all made my PhD journey so much more enriching and fun. I am thankful to my friends Rajeev Jha and Daizzy at the call center for their complete co-operation. Thank you for believing in me and my research abilities.

Finally, I would like to thank my partner and personal cheerleader Trinayan Geet Barua for always pushing me to achieve higher. Your everyday care and support over these years, through every possible mode of communication is what kept me going.

Education makes us the human beings we are. It has major impacts on economic development, on social equity, gender equity. In all kinds of ways, our lives are transformed by education and security.

- Amartya Sen, 2004

ABSTRACT OF THE DISSERTATION

Essays on Labor Supply and Firm Productivity in Developing Countries

by

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Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, June 2020
Dean Anil Deolalikar, Co-Chairperson
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This dissertation presents three independent research projects. The first chapter of this thesis studies the impact of gender composition of teams on employee productivity, using a randomized controlled trial. The study was conducted in Indian call centers located in five Indian cities. This is the first study to estimate the causal impact of opposite gender peers on performance in the workplace setting. For identification, call center employees were randomized into either mixed gender teams (30-50% female peers) or control groups of same gender teams. The study finds precisely estimated zero effects on both productivity (intensive margin) and share of days worked during the study period (extensive margin) of being assigned to a mixed gender team. There is evidence that conditional on being assigned to mixed gender teams, men with progressive gender attitudes have higher productivity than men with regressive gender attitude. There is an overall increase in the secondary outcomes of knowledge sharing, dating and comfort with the opposite gender for male employees in mixed gender teams, relative to all male teams.

The second chapter also uses the setting of Indian call center industry, and studies the impact of air pollution on productivity. Air pollution above the threshold 35.4 µg/m ^{3} $PM_{2.5}$ is viewed as harmful according to both WHO and EPA guidelines. The study finds that days on which pollution is above the threshold, average productivity decreases by 0.19 standard deviations. The study also finds evidence of efficiency loss on high pollution days.

The third chapter studies the effect of co-residence with parents-in-law on female labor force participation (FLFP) in India. Using two rounds of nationally representative panel data of women, death of healthy parent-in-law is taken as an exogenous shock to co-residence with parent-in-law. The paper provides evidence that death of a father-in-law leads to a 11.2 percentage point or 25% increase in FLFP. There is also an increase in FLFP by 11 percentage points following the loss of a working mother- in-law, providing evidence of an added worker effect in the household. On the secondary outcome of empowerment, death of mother-in-law increases women's empowerment by 16.7%.

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Chapter 1

Gender Peer Effects in the Workplace: A Field Experiment in Indian Call Centers

Abstract

Several theories suggest that gender integration in the workplace may have negative effects in gender-segregated societies. This paper presents the results of a randomized controlled trial on the effect of gender integration on work productivity. The study was implemented in call centers located in five Indian cities. A total of 765 employees were randomized to either mixed gender teams (30-50% female peers) or control groups of same gender teams. I find precisely estimated zero effects on both productivity (intensive margin) and share of days worked during the study period (extensive margin) of being assigned to a mixed gender team. However, there is an overall increase in the secondary outcome of peer monitoring and team support for women assigned to mixed gender teams relative to the control team. For male employees, I find that conditional on being assigned to mixed gender teams, men with progressive gender attitudes have higher productivity than men with regressive gender attitude. There is an overall increase in the secondary outcomes of knowledge sharing, dating and comfort with the opposite gender for male employees in mixed gender teams, relative to all male teams.

1.1 Introduction

In the last two decades, the female labor force participation rates have been declining in most South Asian countries, including India (ILO, 2017). This is in contradiction to the female labor supply trend observed in the rest of the world during the same period. Additionally, most occupations in South Asian countries [17] and the world [20] are gender segregated with women sorting into lower paying and lesser skill intensive jobs than their male counterparts. Removing the barriers to entry in the workplace for women in these developing economies will be crucial in boosting their labor supply [21, 20]. However, adverse gender norms and gender segregation practices in South Asia may further increase these entry barriers and make firms skeptical of integrating women into the workplace [13].[1]

Several theories suggest that gender integration in the workplace may have negative effects in gender segregated societies. For many boys and girls in such traditional societies, the very first prolonged interaction (as equals) with the opposite gender, outside of family members happens in a workplace.[2] Interaction among opposite genders is likely to lead to psychic costs in the workplace in such a setting [3, 10]. This can have a negative impact on a firm's output if it comprises of a gender diverse employee pool, especially of young workers. There can be negative externalities of distraction in such a setting [23, 39]. On the other hand, gender diversity in the workplace can enhance competition, monitoring

[1] According to India Human Development Survey (IHDS), a nationally representative household survey, over 58% of married women in India reported to be practicing purdah or seclusion of women from public observation. Around 52% of the respondents in my sample report that their mother or some other female family member practices burkha/purdah.

[2] Even in coeducational schools, peer groups are institutionally determined by gender, by segregation of boys and girls in classrooms. In my sample, around 30% of people at baseline did not interact with the opposite gender outside of their family, while in school. They either didn't attend a co-educational school or if they did, boys and girls in these schools were not allowed to sit together.

and peer pressure among same gender peers if the workers want to impress the opposite gender co-workers [31]. The positive impacts can also be driven by knowledge spillovers and mutual learning which can increase worker productivity in diverse groups [23]. Therefore, these competitive pressures could lead to either positive or negative impacts on a worker's performance in mixed gender work environments. These impacts could be especially be negative for work performance of female employees in such competitive settings [41].

The paper uses an individual level randomized controlled trial in Indian call centers to study the effect of opposite gender co-workers in the workplace on work performance of employees. I randomize employees in call centers in five cities in India into mixed gender (30% to 50% females) and same gender teams. For male employees, I compare the productivity of those assigned to mixed gender to those assigned to all male teams (control group). For female employees, I compare productivity of those assigned to mixed gender teams relative to those in all female teams. The study has a higher number of male employees due to low proportion of female employees in the sample. This is because the female labor force participation rate is low in India so there are fewer women in the workplace relative to men. The randomization increased/intensified opposite gender exposure for male employees in mixed teams and reduced it in the control group relative to the status quo at baseline. A total of 765 employees (297 male employees in mixed gender teams and 320 in all male teams and 67 female employees in mixed gender teams and 81 in all female teams) were seated with their new teams for a median of 12 weeks. Male and female co-workers in mixed gender teams were mapped to sit on alternate seats. The daily level administrative data on productivity, which is internally collected by call centers through automatic technology is used to study worker productivity. So, this paper uses accurate, uniform and consistent measures of productivity for all workers.

A team is an important entity in call centers. In a typical call center, customer support employees or agents are grouped to form teams and agents interact with their team members on a daily basis in team meetings. As it is standard practice in call centers for teams to be seated together, changing the gender composition of teams leads to change in the gender composition of peers seated around a worker. Workers interact with agents sitting next to them if they get stuck on a call and the team leader or manager is not around.[3] This interaction between nearby sitting agents takes place while waiting for calls in the inbound processes. In the outbound processes, the agents typically take out time between calls to talk to agents seated around them.[4] The importance of peer effect in this setting is supported by evidence from the economics literature that low-skilled or routine tasks have significant and larger peer effects than high skill-intensive jobs [14, 29, 7].

The daily level productivity data from both inbound and outbound businesses or processes, are aggregated to create a standardized index for productivity. The top three productivity variables are chosen for each of these kinds of processes after discussion and consensus with the call center heads and the managers. After combining these three productivity variables, the aggregate productivity is standardized within each process. The

[3] Humanyze, a Boston based company uses sensors to analyze communication patterns among employees in the workplace in retail, pharmaceutical and finance industries. In an interview with the Wall Street Journal, the company's CEO reveals their finding that immediate neighbors account for 40% to 60% of everyday interactions for a worker, including face-to-face chats and email messages. There is as low as a 5% to 10% of average interaction per day with someone sitting two rows away. (https://www.wsj.com/articles/no-headline-available-1381261423 accessed in October, 2019)

[4] 66% of the respondents in the baseline survey agreed that they learnt something from the agents sitting next to them. When asked about whose help they seek when stuck on a call at the baseline, a vast majority of agents responded that they took help from the team leader (67%) followed by agents seated nearby (27%) and then others (6%).

second primary outcome used is share of days worked during the course of the study period. This is an unconditional measure based on showing up to work so there are no selection concerns.[5]

My main finding is that there is no effect on both productivity (intensive margin) and share of days worked during study period (extensive margin) of being assigned to a mixed gender team. Given that these are precisely estimated effects, these are important findings as they provide supportive evidence for integrating women into the workplace. It does not seem that hiring women will be costly for the firms, as there is no negative impact on productivity or on share of days worked during study period if assigned a seat next to an opposite gender employee. I also explore whether these findings are true for all kinds of workers.

My second finding is that conditional on being assigned to mixed gender teams, women with high autonomy have higher proportion of days worked in the study period than women with low autonomy. Furthermore, women with higher autonomy had a higher proportion of days worked of about 0.08 percentage points when assigned to mixed gender teams. This result provides evidence that there is some peer effect on the extensive margin of productivity for female employees, but only for those with relatively high empowerment and decision making.

My third finding is that conditional on being assigned to mixed gender teams, male employees with regressive gender attitudes have significantly lower productivity than those with progressive gender attitudes. This indicates that interaction with women may be costly for men with regressive gender attitudes. The significant positive impact of gender

[5] A further assumption of monotonicity is made to avoid selection effects (Lee, 2002).

integration on male employees with progressive gender attitudes on the other hand, is useful evidence supporting gender interactions, especially for policy makers.

My final set of findings explore secondary outcomes using survey response at endline. There is strong evidence of knowledge spillover and learning of 0.3σ (standard deviations) for male employees assigned to mixed gender teams relative to control. The female employees don't exhibit any knowledge spillovers in the treatment. For female employees, there is increase in peer monitoring and comfort for those assigned to mixed gender teams. The female workers in mixed teams received 0.22σ (standard deviations) more peer monitoring and support relative to the control group. This indicates that male employees learn from female agents seated next to them, female employees feel comfortable around these men and are willing to share their knowledge with them. The male employees assigned to mixed gender teams are also significantly (around 16%) more comfortable while receiving feedback infront of opposite gender coworkers in mixed gender teams, than those in all male teams. I fail to find any treatment effects on gender attitude and job satisfaction for both male and female employees.

There is also evidence of an overall increase in dating and socialization by 35% for male employees assigned to mixed gender teams. In India, more than 90% of the marriages are arranged by the families (Centre for Monitoring Indian Economy, 2018). There is high prevalence of caste-based segregation and intra-caste marriages, especially among the poor. The increase in dating for men in mixed gender teams in the setting of small town India (Patna, Udaipur and Hubli) is an important finding.

The study contributes to multiple threads of literature. To my knowledge, it is the first individual-level randomized controlled trial to causally interpret the effect of gender diversity of teams on employee performance.[6] It builds on the literature on performance of gender diverse business teams comprising of students. These studies change the gender composition of group homework or project teams in undergraduate or graduate management classes and look at group level outcomes of students [27, 24, 6]. They find that equal or mixed gender teams outperform male-dominated and female-dominated teams. An associated thread in the literature studies gender diversity in boardrooms [9, 1, 2, 40]. Their outcome measures are firm's value/profits and gender earnings gap. Some studies find a favorable change in gender attitudes of males due to gender integration in the workplace in developed country work place settings [15, 18]. However, this RCT looks at individual level productivity measures as outcomes. Furthermore, all these papers address this question in a developed country setting. This research question is more relevant in the context of a developing country workplace, where gender is salient. This paper also adds to the thread of experimental studies set in non-work settings in India, which have shown how diversity has been successful in removing inter-group biases [43, 8, 35].

Human resource allocation in the workplace such as seating and team alignments, which maximize worker productivity are integral to the workplace and personnel management literature [32]. There is a broad literature of experimental studies that test workplace heterogeneity and socialization in the workplace. This paper adds to these studies that test the effect of diversity along ethnicity [26] and nationality [37] lines on employee perfor-

[6] Randomization of team composition solves the endogeneity and selection problems associated with team formation and also resolves Manski's reflection problem [38]

mance. It also contributes to studies testing the impact of social pressure, social incentives and social networks on worker productivity [29, 39, 7, 4, 42].

This study complements the large literature on impact of differential gender composition in classrooms on schooling outcomes of students. They find evidence of gender peer effects on educational outcomes in kindergarten [45], elementary school [28], middle school [34, 36, 11, 22], high school [33, 30] and college level [25]. There are some studies which find no effect of higher proportion of opposite gender in classrooms on male student's test scores or passing rates [5, 12].

My findings have broad policy implications for integrating women into the workforce. Even in the context of this study, some of the sample call centers receive financial subsidy from the central government under India BPO Promotion Scheme (IBPS) to open up its branches in smaller cities.[7] The government of India is committed expanding BPOs to smaller cities, with special provisions of incentive in IBPS for hiring women in order to boost female labor force participation. Due to this scheme and the lower minimum wage requirement in smaller towns, there are now many call centers opening up in smaller cities in India. The evidence from this study can further add to the knowledge of the state and firms and promote hiring of women in the smaller towns of India.

1.2 Call center setting

The field experiment took place in two Indian call center companies: Call-2-Connect India Pvt. Ltd. and Five Splash Infotech Pvt. Ltd. Call2Connect India Pvt. Ltd. has centers in the state of Bihar (Patna), Uttar Pradesh (Noida) and in a metropoli-

[7] India BPO Promotion Scheme https://ibps.stpi.in/ (last accessed on 23rd September, 2019)

tan city in Maharashtra (Mumbai). Five Splash Infotech Pvt. Ltd. has centers in the state of Rajasthan (Udaipur) and Karnataka (Hubli). All these five cities/locations were used in this experiment.

Business Process Outsourcing companies perform certain contractual tasks or responsibilities for other companies in order to help them to run smoothly. They provide both voice and non-voice support to other companies. So, a call center usually has multiple processes/tasks. The call centers in my study are domestic call centers, providing voice support to local customers in different kinds of processes. The voice support processes that they deal with are broadly divided into inbound and outbound processes. The inbound processes provide customer support services to incoming calls. The inbound processes in sample call centers provide help to all kinds of companies such as food delivery, financial technology, beauty retail etc. In outbound processes, calls are made to customers to mostly make sales. In my sample, outbound calls are made during elections by a political party as part of their campaign/advertisement. I have five inbound and five outbound processes in the study.

1.2.1 Background on call center employees

The entry level BPO employees who make or receive calls are known as agents. Any incoming agents/employees get hired for training on the recommendation of the human resource team after an interview. As the processes in the study are all dealing with domestic customers, the entry-level worker requires local language spoken skills and some basic computer training for the job. They are then trained usually for 5 to 10 days by the training team, depending on the process requirement. They are taught the call script, the call quality parameters such as courtesy on the phone, how to use the headsets and computer software related to the process. After the training, they are required to take a test to get certified to be an agent for a particular process. If they fail the test, they have to leave. The training period is unpaid in many domestic call centers.

After an agent gets hired, they work 6 days a week with one day of the week as a holiday (chosen by the agent). A regular workday for a full-time working agent involves 8 hours of logged-in time where the agent is active and available to take calls and one hour of break. Each agent is allocated a computer system with the process information software and a headset. In my sample, when an agent came to work (prior to the period of the study), she had to look for a vacant seat in the assigned seating area for her team and then login into the system with her unique identification number and password. The incoming or outgoing calls are flashed on the computers of agents through a computerized call queueing system. The agents cannot miss any calls if they are logged-in and idle. When it is an agent's time for a break, they can log out of the system. Usually the entire team cannot take lunch breaks together, especially in customer support services where a certain number of agents are pre-decided to be logged-in at different times of day. This is based on expected call volume during the day.

In a typical call center, agents work in teams helmed by the team leader/supervisor. Team leaders supervise groups of 20 to 25 agents (team size), and provide those agents with feedback about their performance using real-time information. The members of a given team leader sit together, taking up 2-3 isles, making it easier for team leaders to monitor agent performance and conduct on-floor team meetings. The agents are usually allocated to the team leader but in many cases, the team leaders give their preference of agents from a new batch of newly qualified workers. The team leaders in the chosen centers are mostly male. The job role of the team leader also includes providing emotional support and motivating the agents, incase of rude and difficult customer experience. Assistant managers, also known as the operations manager, supervise the team leaders.

Agents are paid a fixed salary every month and rarely receive additional incentives. In my sample, the agents are paid an approximate salary of $100-150 per month in smaller cities and $150-220 per month in metropolitan cities with a rare scope of earning $15-20 extra per month depending on call volume. Based on performance, agents get eligible to become team leaders after six months of experience and they get a salary hike of anywhere between 30 to 50 % upon promotion.

1.2.2 Advantages of the call center setting

There are many advantages to choosing call centers to conduct this experiment about the impact of gender composition of team members on employee performance. This industry serves as an ideal setting for this study. First, despite most industries and occupations in India being male dominated (Mondal, 2018) , the call centers or the Business Process Outsourcing (BPO) sector employs large number of female employees at the agent level (entry level jobs involving making calls as customer support representatives) due to their comparative advantage in interpersonal skills (Jensen, 2012). About 50% of the BPO employees are women in Tier-1 cities and about 20% to 40% in Tier-2 cities in India.[8]

[8] There is tier-wise classification of centers in India based on population into Metropolitan (Tier-1), urban and semi-urban centers center (Tier-2, Tier-3 and tier-4) and rural centers (Tier-5 and Tier-6)

Second reason for choosing this setting is that this is an entry level job and employs young people with low prior exposure to opposite gender. The average age of an agent is around 21 years in my sample. Since most employees are hired straight after high school, they have low past exposure to the opposite gender. This is because even in co-educational schools, peer groups are institutionally determined by gender, by segregation of boys and girls in classrooms. In my sample, around 30% of people at baseline did not interact with the opposite gender outside of their family, while in school. They either didn't attend a co-educational school or if they did, boys and girls in these schools were not allowed to sit together. Domestic call center agents are used for this analysis as it is expected that they have relatively lesser exposure to opposite gender compared to English speaking call center agents catering to international clients.

A third reason is that there are productivity measurement advantages in this setting. First, technology-based monitoring allows for consistent and exact measures of productivity. Second, all agents are aware of these top productivity variables and are provided routine feedback on their individual performance on these variables. So, there is no kind of information asymmetry about the productivity parameters, targets and performance for some agents and not for the others. This is important to avoid any systematic bias in effort of some agents due to lack of information. Third, agent's incentive/pay is not tied to her group performance. This helps in getting rid of any productivity measurement concerns arising from free riding problems. Fourth, these productivity variables are important for the call center profitability so the results of this analysis are of interest and are crucial to the successful operational management of these firms.

The final reason is that the features of this workplace resemble other workplace settings across the world. Workers sit in cubicles next to each other and perform individually assessed tasks. So, the results of this study have implications for other work settings beyond this specific industry. In the context of the call center industry setting, it is the largest private sector employer in India, providing jobs to around 3.9 million people (NASSCOM2017). The call centers in my study are located in both metropolitan and small cities in India. The chosen call center partners had a similar management structure to other call centers in India that were contacted in the course of this study. Some of these call centers also receive a subsidy from the central government (India BPO Promotion Scheme (IBPS)) for opening centers in Tier-2 and additional incentive for hiring female employees. Therefore, the call centers are beginning to spread into small towns to avail this subsidy and to cut costs.

1.3 Experimental Design

This RCT experimentally alters the gender composition of teams to study gender peer effects in the workplace. This section discusses the selection criteria of the the call centers, randomization design, main outcomes and their data collection, empirical specification and balance tests of randomization. The importance of teams in this setting is also discussed, along with the team bonding exercise which was carried out to increase knowledge spillovers among new teammates.

1.3.1 Selection of study subjects

Agents from two BPO companies located in total five Indian cities were chosen for the study. The study took place in 9 businesses/processes within these five centers. There were several criteria for selection of these processes.

A challenge of the call center setting is that there is very high attrition - around 10-20% in smaller cities and as high as 30-40% in metropolitan cities. To circumvent this problem, most of the call centers chosen are in small cities (Udaipur, Patna, Noida and Hubli), so they experience lesser attrition. This also made it possible to study diversity impacts on productivity across many states in India. In addition, the employees in small towns are expected to have minimal opposite gender contact outside their family.

Another challenge is that most workplaces in India and these domestic call centers is that they do not employ female employees in the evening shift. This is because labor laws in India prohibit companies to employ women after 7 pm, unless special approval is taken and sufficient security and conveyance is provided to the female employees. To cut costs of arranging transport for female employees, the centers avoid hiring female employees in evening shifts. So, full-time, morning shift agents are used for the analysis.

An important reason for choosing these particular centers was that there was gender diversity in these centers and men and women were working together in the same shifts. This allowed me to construct mixed gender teams. These centers had one or more processes with atleast 60 agents (3 teams). In order to conduct this experiment, construction of three teams (two mixed and one same gender team) was needed, which could be formed with a process size of atleast 60 agents managed by three team leaders. In some ideal cases, four teams could be formed and the gender composition of the process was almost equal with similar numbers of men and women. The four teams that could be formed were two mixed gender teams, one all-male team and one all-female team.

The processes that met these criteria were chosen to be in the study. Three processes from a call center in Hubli (from the state of Karnataka), two processes from Noida (Uttar Pradesh), two processes from Patna (Bihar), one process from Udaipur (Rajasthan) and one from Mumbai (Maharashtra) were selected. Out of the chosen locations, Mumbai is the most developed and is categorized as a metropolitan and Tier-1 city. Hubli, Noida and Patna are less urbanized and are in the Tier-2 category. Udaipur in the state of Rajasthan is in Tier-3 category. The North Indian states of Bihar, Rajasthan and Uttar Pradesh in my study are known to perform poorly on the gender equality index than the South Indian states of Maharashtra and Karnataka (SDG India Index Baseline report, 2018).[9]

In processes with more than 60% males, two mixed-gender teams and one all male team is constructed (See Figure 2). This is so that the total number of male employees in the two mixed gender teams is approximately equal to the total number of male employees in the same gender team. If the size of the process allowed for the formation of a fourth team, all female teams were constructed (See Figure 1). There is one morning-shift process where there were greater number of female employees than male employees (See Figure 3). In this process, two mixed gender and one all-female teams were formed. There are three all female teams in the sample, with allocation in three different processes. When the study

[9]SDG Index developed by the United Nations and Niti Ayog, Government of India, for gender equality included sex ratio at birth, average female to male wage gap, percentage of seats won by women in general elections, percentage of ever married women who experienced intimate partner violence and percentage of women using modern methods of family planning. Bihar, Rajasthan, Delhi and Uttar Pradesh were at the bottom ten and Karnataka and Maharashtra were in the top ten on this index.

began, the existing agents were aligned into teams for 6 to 14 weeks. The new batches of employees that joined the processes in the course of the study were also randomly assigned into teams.

1.3.2 Randomization

I use matched pair randomization method based on past productivity data to assign individual agents into teams. Same gender agents belonging to a particular work-shift are matched on their average performance. The average performance is calculated on one of the chosen (by the company) productivity parameters from 3-4 weeks of pre-study administrative data. These matched pairs of male agents are then assigned into either treatment group (mixed gender team) or control group (male team) using random number generator. The female employees are randomized into the various mixed groups using random number generator. The same method of matched pair randomization is followed in centers where female-only teams could be formed. The teams were made to sit for 6 to 14 weeks based on status of the process.[10]

This batch of existing employees that was randomized on past productivity, will be called the old batch. There were new batches of employees that joined during the course of the study and in the absence of information of past productivity, random number generators were used to assign them into teams. The team sizes and gender proportions were maintained during these assignments. One of the processes in Patna was less than

[10]The experiment went on for 12 to 14 weeks in most call centers -8 out of the 10 processes. One of the each process in Patna and Noida was shut down by the contracting company so the study could run for 6 and 9 weeks respectively in these processes.

a month old process so there was no information on past productivity available when the team alignment took place. This process will also be called a new batch.

The same method of matched pair randomization is followed to assign team leaders into treatment and control teams. The team leaders are first matched on the past performance based on the average performance of the agents working in their team in the pre-study period. One of each of the matched team leaders are assigned randomly to either treatment or control group.

Prior to the study, flexible seating was followed in all the call centers. In the duration of the study, seat was assigned wherever possible. In four inbound processes and one outbound process, fixed seating assignments were followed. The seats were decided using a random number generator. It was ensured that male and female employees in mixed gender teams were assigned alternate seats. There were five outbound processes, where fixed seating assignments could not be followed. However, even with flexible seating followed within teams in these processes, it was ensured that male and female employees in mixed gender teams sat on alternate seats. There was monitoring at the daily-level to check if the seating plan was followed.

1.3.3 Teams in call centers

Team is an important entity in call centers. Even though it is individual-based work, the industry promotes bonding among team members and encourages interaction among opposite gender employees. This is crucial for mutual learning and potential knowledge spillovers within teams. In the call centers in my sample, the job training involves trainers conducting interactive games among opposite gender trainees. They carry out these interactive games to enhance communication and comfort among opposite gender employees on the work floor. The training teams also deploy various kinds of mixed-gender seating plans in the training rooms for this purpose. However, usually the training period is very short and not sufficient to break the gender barriers.

Once the agent comes to the floor, there are daily team meetings, usually in the morning, in which team members receive feedback from their team leader on their previous day's performance. The interaction between nearby sitting agents also takes place while waiting for calls in the inbound processes. In the outbound processes, the agents typically take out time between calls to talk to agents seated around them, since they can't move around on the floor to socialize.

In order to further strengthen the bonding between the newly constructed teams, a knowledge-sharing game was conducted.[11] There are quality auditing teams within call centers which listen to about 10-20% of randomly selected calls and give performance scores to these calls based on a pre-decided metric. With the help of these quality auditors and training teams, three calls recordings were selected - a call with excellent quality score, a call with average score and a call with low score. As part of the study, these three calls recordings were shared on the computer systems of agents using google drives for one full workday. The agent were given a small notebook in which they had to note down the strengths and shortcomings of the call, their suggestions for improvements and any call-related issues they had faced in the past. They were given 5-7 most important process-based quality criteria.[12]

[11] A challenge was that all the team members could not leave the floor together at any given time in the day and the call centers requested that the game be conducted in less than half an hour.

[12] The call recordings and quality parameters were chosen by the managers and quality auditors of each call center. The agents rated the calls on broadly these quality parameters 1) opening and closing salutation/verbiage, 2) listening skills, 3) rapport building with the customer, 4) soft skills such as courtesy and empathy, and 5) product and process knowledge.

Whenever the agents were waiting for calls, they would listen to these call recordings and make notes.

Using a random number generator two members from a team were selected to be 'buddies.' From mixed gender teams, opposite gender employees were chosen to be buddies. Team bonding exercises were played under the supervision of the research team and the quality auditor in the conference room of the call center. Each set of buddies were made to sit across from each other and asked to discuss and share their ideas on the aforementioned points. The objective of the exercise was also to promote work-related conversations.[13]

1.3.4 Main outcomes and data collection

The primary outcomes studied in this paper are work productivity and share of days worked in the study period and the secondary measures are gender attitude, job satisfaction, knowledge sharing, dating, peer monitoring and support and comfort with the opposite gender. This study relies on various sources of data to study these outcomes: (i) a baseline survey, (ii) administrative data from the firm, (iii) a follow-up survey at the end of the study. The baseline data was collected before the randomization took place through 30-40 minute long online survey of all agents within a process. The agents took this online survey on their office computer systems in the presence of a member from the survey team on-site. All agents within a team could not take the survey at once so team members took the survey one at a time. The surveys took place usually in late afternoon or evening, as there was lesser call volume during that time of the workday.

[13]The learnings from this exercise about work related issues faced by the agents and the gaps in training were shared with the management. They found it to be helpful in improving their training and operations.

Baseline information was collected on family, education and employment background; gender exposure and empowerment questions on past interaction with opposite gender, autonomy and gender attitude, and potential mechanisms of stress, comfort in teams, self-esteem, socialization etc. At the endline, right before the study ended, there was a short 15-20 minute online survey on the secondary outcome measures and the aforementioned potential mechanisms. For processes in the first half of the study timeline, endline data could not be collected for everyone in the sample as most of the agents had left by the end of the study period. This was due to generally high attrition rates in this industry. For the second half of the sample, the agents who had left the study midway were tracked and requested for a survey response. So, the endline data is used only for the six processes in the second half of the study.

For the main outcome of productivity, individual level daily performance data internally collected by the call centers is used. These measures of productivity are collected automatically by the call center's technology-based monitoring system. The main outcome measure will be the aggregate of the top three quantitative measures of agent productivity, typically used by the call center to track performance. The exact measures used depended on whether the agent worked in inbound or outbound processes.

The inbound processes provide customer support services to incoming callers, so their main productivity measures are average call handling time (ACHT), number of calls and net login hours. The firms gain profits if the agents receive a high number of calls, login successfully for at least 8 hours and handle the calls in less amount of time. So, ACHT is signed as negative in the data.

In outbound processes entailing sales calls, the primary productivity variables are total sales made per day, total calls made per day and their ratio of total sales by calls made per day. The firms gain profits if total sales made per day increases and if the ratio of sales by calls also increases per day. So, the firms benefit if an agent has a high sales conversion rate of calls i.e., she achieves daily sales targets by making fewer number of calls. The total number of calls made per day in the outbound processes is therefore signed as a negative.

Each individual productivity measure is standardized (with mean zero and a standard deviation of one) relative to performance of members of the control group in a respective process. These measures are aggregated for each process and then standardized again using control group mean and variance. Thus, the outcome measure of productivity is comparable across processes.

The second main outcome is share of days present in the study period. In the daily level administrative productivity data, there is information on the productivity of all the logged-in agents on any particular date. This gives information on who was present and absent on each particular day of the study from the day of joining the study. Using this, each agent is marked to be present on the days in the study for which their productivity data is available and for other days, they are marked absent. Hence, share of days worked during study period is calculated as:

$$Share\ of\ days\ worked\ during\ study\ period = \frac{Days\ present\ in\ the\ study\ period\ from\ joining}{Number\ of\ days\ of\ the\ study} \tag{1.1}$$

The first secondary outcome measure of gender attitude is studied. A broad set of questions are borrowed from the current literature on measuring women's empowerment and gender attitudes [16, 19]. The broad topics covered in these questions are education attitude, employment attitude, attitudes on traditional gender roles and fertility attitudes. Each individual worker in the study is surveyed on these questions prior to the start of the study (baseline) and towards the end of the study (endline). A standardized index is formed each at the baseline and endline using control group mean and standard deviation.

Another secondary outcome measure focused in the study is the job satisfaction level of employees. It is collected at an individual level through baseline and endline surveys. To determine job satisfaction, each employee is asked to evaluate her "emotional exhaustion" using a standardized set of questions [44]. The responses to these questions standardized and are aggregated to form an index, using control group mean and standard deviation.

Knowledge sharing within teams, peer monitoring and support, dating and comfort while receiving feedback infront of opposite gender are other important secondary outcomes studied. The individual employees were surveyed on these outcomes both at baseline and endline. Only for the outcome, comfort while receiving feedback infront of opposite gender, baseline data was not collected. Mid-study qualitative survey of managers about the expected impact of the study highlighted that male employees felt uncomfortable while receiving feedback from the team leaders infront of female employees, especially if the feedback is negative. Therefore, this additional question was asked at the endline. The exact questions asked for these variables is mentioned in the Appendix in the survey questions section.

For all secondary outcomes, individual level survey responses collected at endline for five of the nine processes in the study involving male employees is used for the analysis. The endline data could not be collected for the entire sample for four processes due to attrition during the study period. For the sample of five processes for which endline data could be collected, workers were followed and surveyed even after they quit employment at the call center in the study duration. For female employees, the endline responses could be obtained for all the entire sample involving three processes.

1.3.5 Empirical Specification

To measure the average impact of treatment/gender exposure, I use intent-to-treat (ITT) effects by regressing productivity and other outcomes on an indicator for mixed gender team or gender integration treatment. All the outcomes have either multiple time-period data or the same question was asked in both the baseline and follow-up surveys. The main specification is the following ANCOVA specification to obtain β_1:

$$\begin{aligned} \mathrm{Y}_{igst} = \beta_0 + \beta_1 \mathrm{GenderIntegrationTreatment}_{igst} + \beta_2 \mathrm{Y}_{i,PRE} \\ + \omega_s + \upsilon_t + \mathrm{MissingBaselineData}_{igs} + \epsilon_{igst} \end{aligned} \tag{1.2}$$

Where $\mathrm{Y_{igst}}$ is the given outcome variable measured post-treatment, and 'i' is agent, 'g' is team/group, 's' is strata or the lowest unit of randomization (either pair, shift, batch or process) and 't' is date. Gender-Integration-Treatment$_{\mathrm{igst}}$ is an indicator for the individual being assigned to treatment arm. $\mathrm{Y_{i,PRE}}$ is productivity of agent 'i' in strata 's' at baseline. For employees whose baseline productivity data is missing, the control mean value of 0 is assigned to them. Missing Baseline Data_{igs} is an indicator variable which takes the value 1 if the employee was a new entrant and did not have any baseline productivity information at the time of randomization, and it takes the value 0 if the employee had baseline information. ω_s is strata fixed effect, υ_t is date fixed effect and ϵ_{ist} is the error term. Standard errors are clustered at the team level to account for any correlated shocks to productivity within teams.

This specification is run separately for male and female employees in the study. There are 38 teams/clusters for male agents and 8 clusters for female employees. In cases where an outcome variable was not collected at baseline, these same specifications is estimated without the control for baseline outcome.

1.3.6 Randomization and Implementation Checks

Balance checks in Tables 1and 2 show that the randomization was successful on baseline productivity and other individual characteristics of the sample. These balance checks are conducted after controlling for strata fixed effects (unit of randomization). The most important variable for balance is baseline productivity and it passes the balance test by failing to reject the null hypothesis that there is no difference between the treatment and control groups. There were some employees who left the call center before the study began. They were included in the initial randomization because the call centers provided old employee lists or failed to remove the employees who had submitted their resignation prior to the randomization. Therefore, a selective attrition test is also conducted on the remaining sample of male employees after accounting for attrition. Appendix Table 1 shows that the treatment and controls arms were balanced on individual characteristics after removing attriters.

1.4 Results

This section presents the results of the RCT on primary outcome measures. The evidence on the extensive margins of productivity, share of days worked during the study period is presented. On the intensive margin, impact on daily worker productivity is studied. Heterogeneous effects of treatment is also highlighted in the second subsection followed by the results on secondary outcomes.

1.4.1 Results on primary outcome measures

For both male and female employees, there is no overall impact of being assigned to gender integration treatment on share of days worked during the study (Table 3). The control mean for male employees is 0.49 or male employees in the control group worked for around 50% of the days of the study. The effect of being assigned to a mixed gender team meant a reduction of proportion of days worked by approximately 1.6% compared to workers in all male teams (Table 3, column 1). The estimate is insignificant and is a precisely estimated result with tight bounds around zero. The standard error is of 0.023 for male employees. The null value lies within 95% confidence interval [CI -0.037 to 0.053] around the point estimate.

The female workers assigned to the control teams worked for a higher proportion of days of about 56% in the study duration, than their male counterparts. The impact of being assigned to mixed gender teams relative to same gender teams for females is approximately

1.4% of lesser share of days worked during the study period (Table 3, column 3). The standard errors for female employees at 0.042 is slightly larger than that for male employees, because the sample size for females is smaller in the study. However, the effect of gender integration treatment on share of days worked during study period for female employees is also not distinguishable from zero [95% CI -0.074 to 0.09].

The overall effect of gender integration treatment on productivity is zero for both male and female employees (Table 3). These effects are precisely estimated with tight bounds around 0 at the 95% confidence interval. The impact of being assigned to mixed gender teams on male productivity is 0.017σ (standard deviations) higher than the control mean (Table 3, column 2). The standard error is 0.049 for male productivity and the null value lies within the 95% confidence interval [CI -0.08 to 0.11].

For female workers, the overall impact of gender integration treatment on daily productivity is -0.08σ (standard deviations) lesser than than the control group (Table 3, column 4). With standard error 0.048, this is an insignificant result with the point estimate falling between the 95% confidence interval [CI -0.13 to 0.17]. These estimates allow me to rule out gender peer effects on productivity that are fairly small.

1.4.2 Heterogeneous treatment effects on primary outcomes

I test for heterogeneity along baseline measures of low prior exposure to opposite gender and regressive gender attitude for male employees on the primary outcomes of productivity and share of days worked during study period. An additional characteristic of autonomy or decision making power for female employees is tested (Tables 4 and 5). The survey responses on each of these characteristics are averaged for every respondent (See Appendix section on survey questions) and then the median value of all the responses based on gender is taken as cutoff to categorize same gender workers as high or low in that particular characteristic. I do not find evidence for heterogeneity along these characteristics on share of days worked during study period for male employees (Table 4, columns 1 and 2).

I find that conditional on being assigned to mixed gender teams, women with high autonomy have significantly higher share of days worked in the study than women with low autonomy (Table 4, column 5). Women with higher autonomy had a significantly higher proportion of days worked of about 0.08 percentage points when assigned to mixed gender teams relative to the control group mean of 0.56 for all female teams. So, the women with high baseline autonomy showed up to work approximately 14% more than those assigned to control. For other characteristics for females, there is no evidence for heterogeneity on this outcome measure (Table 4, columns 3 and 4). These results suggest that there are no gender peer effects on the share of days worked during study period for workers with low or high past exposure to opposite gender and workers with regressive or progressive gender attitude.

While testing for heterogeneous treatment effect on daily level employee productivity, I find that conditional of being assigned to treatment male employees with regressive gender attitude have significantly lower productivity than those with progressive gender attitude (Table 5, column 2). So, males with regressive gender attitudes show up to work for the same proportion of days as men with regressive gender attitudes but have lower daily productivity. I do not find any evidence for heterogeneity along past exposure to opposite gender on productivity outcome, for either male or female employees (Table 5, columns 1 and 3). For female employees there is no evidence on characteristics of attitude and autonomy (Table 5, columns 4 and 5). This indicates that there is an overall zero treatment effect on female productivity along the distribution of these individual characteristics of opposite gender exposure, gender attitude and autonomy/ empowerment.

1.4.3 Results on secondary outcome measures

I explore secondary outcomes using survey response at endline for male employees and find strong positive impacts on knowledge sharing, dating and comfort with opposite gender (Table 6).[14] There is a 0.3σ (standard deviations) increase in knowledge sharing, which measures if the employee benefitted from agents sitting nearby on work related issues (Table 6, column 3). This is a large treatment effect which provides evidence of knowledge spillover and learning for male employees assigned to mixed gender teams. This result is significant at the 5% level. It indicates that male employees learn from female agents seated next to them.

There is an increase of 19 percentage points in dating for male employees in treatment teams, higher than the mean dating of 0.54 in the all male teams (Table 6, column 4). So, there was an increase of 35% in dating for male employees assigned to mixed gender teams compared to the 54% dating in the control teams. This result is significant at the 5% level. However, the reporting is lower for this question as it was the last question of the survey. A pre-intervention balance check was done on individual characteristics for men

[14] For male employees, the endline data is not available for the entire sample but for five of the nine processes. The result for these processes for which endline data is available is similar to the overall results for main outcomes discussed in the previous sections (see Appendix table 2).

who responded to the dating question and those who didn't and the two groups were found to be similar.

I also find a 0.05σ (standard deviations) increase in comfort while receiving feedback infront of opposite gender employees for male employees, relative to the control group mean of 0.32 (Table 6, column 6). This result is significant at the 5% level. The male employees in mixed gender team were approximately 16% more comfortable with the opposite gender than those in all male teams by the end of the study period.

For gender attitude of male employees, there is no evidence of any treatment affect. There is a -0.19σ (standard deviations) decline in the gender attitude of male employees assigned to mixed gender teams relative to the control group (Table 6, column 1). The estimate is insignificant with a standard error of 0.2. It has bounds around zero at the 95% confidence interval [CI -0.58 to 0.19]. For other secondary outcome measures of job satisfaction level and peer monitoring and support, I find similar precisely estimated effects bounding zero. The treatment effect for job satisfaction is a small decrease of -0.01σ (standard deviations) relative to the control group. This result is insignificant and has a standard error of 0.17 [CI -0.18 to 0.16]. The treatment effect for peer monitoring and support is 0.05σ (standard deviations) relative to the control group. This result is not significant and has a standard error of 0.17 [CI -0.28 to 0.38].

For female employees, there is increase in peer monitoring and team comfort for those assigned to mixed gender teams (Table 7, column 5). The female workers in mixed teams received 0.22σ (standard deviations) more peer monitoring and support relative to the control group. This result is significant at the 1% level. So, even though female workers don't have a treatment effect on knowledge spillovers from their teammates or comfort while receiving feedback from opposite gender, they seem to be receiving a lot of support from their male peers if assigned to a mixed gender team. The results on knowledge sharing and comfort with opposite gender are precisely estimated with bounds around zero. There is a decline of 0.11σ (standard deviations) compared to the control group mean on knowledge sharing (Table 7, column 3). This is not significant and with a standard error of 0.14, the point estimate lies within a 95% confidence interval [CI -0.39, 0.17] which bounds zero.

Higher number of female employees reported to be comfortable with the opposite gender (55%) compared to 32% of male employees in the control groups. Female employees belonging to the same gender teams also have a higher incidence of dating than male employees from all male teams by 8 percentage points. I find that the treatment effect of being assigned to a mixed gender team on comfort with opposite gender while receiving feedback is 0.06σ (standard deviations) higher than the control (Table 7, column 6). With a standard error of 0.13, the result is not significant and the point estimate lies within the confidence interval bounding zero [-0.2 to 0.19].

The overall impact of treatment on dating among female employees is quite low at 0.1 percentage point or 1.6%. This is a precisely estimated zero effect with a standard error of 0.16 falling within the 95% confidence interval [CI -0.31 to 0.32] around the point estimate (Table 7, column 4). I find a large but insignificant impact of treatment on both gender attitude and job satisfaction levels of female employees. The effect of treatment on being assigned to mixed gender teams is 0.25σ (standard deviations) higher than the control group with a standard error of 0.14 [95% CI 0.02 to 0.5] (Table 7, column 1). The gender integration treatment effect on job satisfaction level is 0.27σ (standard deviations) higher than the control with a standard error of 0.17 [95% CI 0.02 -0.06 to 0.6] (Table 7, column 2).

1.5 Discussion and Conclusion

This study provides an experimental test of productivity impacts for employees with mixed gender composition of peers in the workplace, against employees with same gender peers. Competing forces of knowledge spillovers, dating and socialization, comfort and peer monitoring are also studied. I find a precisely estimated overall zero effect on daily productivity and share of days worked during study period for both males and females assigned to mixed gender teams relative to control groups of same gender teams.

Research on productivity improvements in the high growth sector BPO industry is crucial for sustainable job creation for many young workers, particularly women. Due to growth and increases in employment opportunities, women who were previously doing unpaid care work or informal work, are entering the formal labor market in regions like Patna and Udaipur. These call centers also attract young workers from nearby villages and small towns. The policy makers in India are interested in expanding this sector to more of these smaller cities and even villages. Under the IBPS scheme, the government gives incentives to firms to open up branches in these smaller places and also provides additional incentive to call centers to hire female employees to boost their labor supply. The paper provides supportive evidence to strengthen the objective of the policy makers. It also informs firms skeptical of integrating women into the workplace that integration of women into the workplace is not costly, as gender diversity and interactions in the workplace do not impact the productivity of a worker negatively.

Even though this study has implications on all kinds of gender diverse workplaces, there might be more positive effects on the intensive margin of productivity in places with lesser gender discrimination and progressive gender attitudes for male employees. Similarly, the treatment effects on extensive margins of share of days worked during study period may be higher for women with higher autonomy. Increases in knowledge sharing, peer monitoring and comfort of receiving feedback infront of opposite gender in mixed gender teams is evidence that there is higher knowledge spillovers in gender integrated settings. Therefore, the firms may benefit from policies of gender-integrated seating, such as the one practiced in the study in mixed gender teams with alternate seating of opposite gender employees in increasing knowledge spillovers and learning for male employees and peer monitoring and comfort for female employees. This may prove a low cost way of increasing learning among coworkers in firms.

In India, more than 90% of the marriages are arranged by the families (Centre for Monitoring Indian Economy, 2018). There is high prevalence of caste-based segregation and intra-caste marriages especially among the poor. The increase in dating for men in mixed gender teams in the setting of mostly small town India, is an interesting finding.

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ACKNOWLEDGEMENTS

The dissertation author is the primary investigator and author of this paper. The RCT was pre-registered at the AEA registry with ID # AEARCTR-0003932.

I am grateful for the invaluable guidance, immense support and unwavering encouragement over the course of this project from my advisors, Anil Deolalikar, Sarojini Hirshleifer and Joseph Cummins. This paper has also benefitted from helpful comments from Steven Helfand, Ozkan Eren, Michael Bates, Carolyn Sloane, Bree Lang, Matthew Lang, Gordon Dahl, Jonas Hjort and the faculty mentors as well as the faculty mentors and selected workshop participants at the Ronald Coase Institute.

I would like to thank the International Growth Center (IGC), BLUM Initiative at UC Riverside and Graduate Division, UC Riverside (Dissertation Year Program Fellowship) for funding this project. I am grateful to the CEOs and center heads of partner call centers, Anil Sinha, Rajeev Jha and Sujit Sharma of Call-2-Connect and Kapil Sharma, Lakhan Joshi and Soham Ghosh of Five Splash for believing in the project and offering their support. I appreciate the help of Ministry of Electronics and IT: Government of India, Software Technology Parks of India and Bihar Industries Association for introducing and recommending this project to call centers.

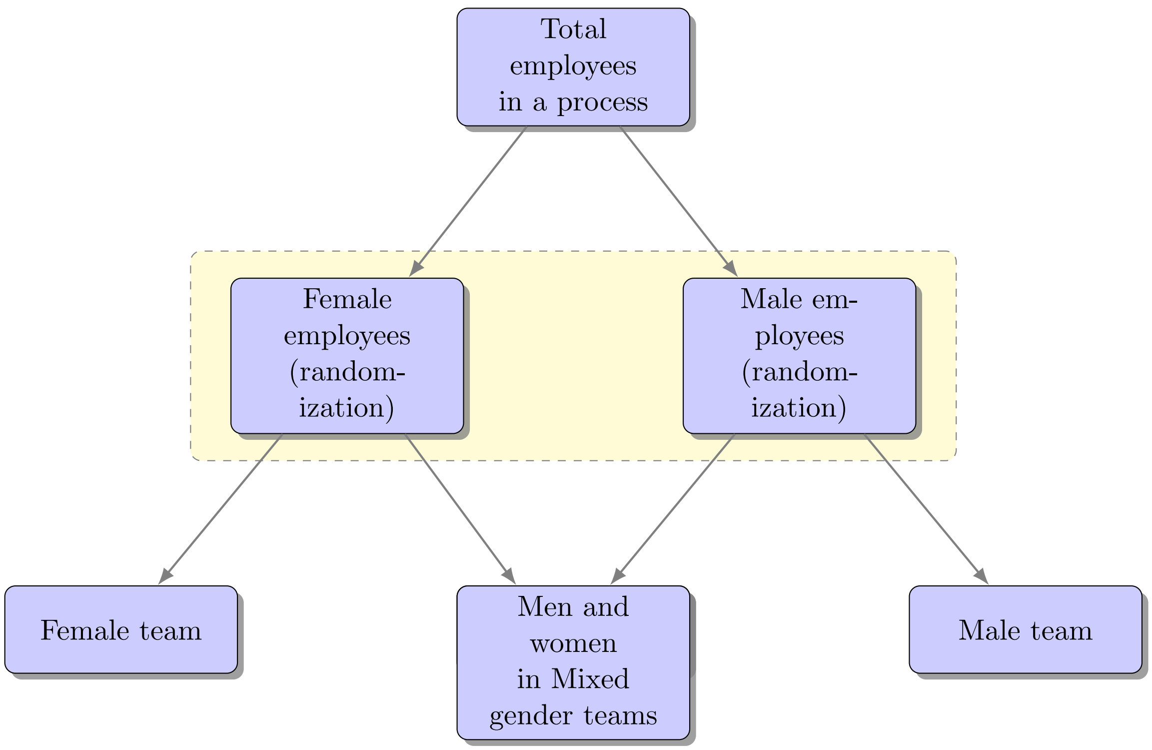
Thanks also to Anil Kumar Vaishnav, Daizzy Sharma, Prabudh Rao Kaushal, Rajat Kumar, Priti Rao and Priyanka Jadhav for their outstanding assistance in data collection. This project could not have taken been completed successfully without the participation of the study subjects and the support of all the team leaders, managers, HR and MIS teams at the call centers.

I appreciate the help of Mr. Anshuman Gaur, Private Secretary to Minister for Law and Justice & Electronics and IT and Mr. Rajiv Kumar, Joint Secretary at Ministry of Electronics and IT at Government of India (MEIT: GOI); Mr. Devesh Tyagi, Senior Director at Software Technology Parks of India (STPI), Mr. Madhurjya Prakash Baruah, Additional Director at STPI and Mr. K.P.S. Keshri, President of Bihar Industries Association (BIA) for introducing and recommending this project to call centers. I also want to thank my friend Vibhu Mishra for helping me connect to call centers.

All views expressed in this paper are those of the author alone and need not necessarily reflect those of the call centers, MEIT: GOI, STPI or BIA.

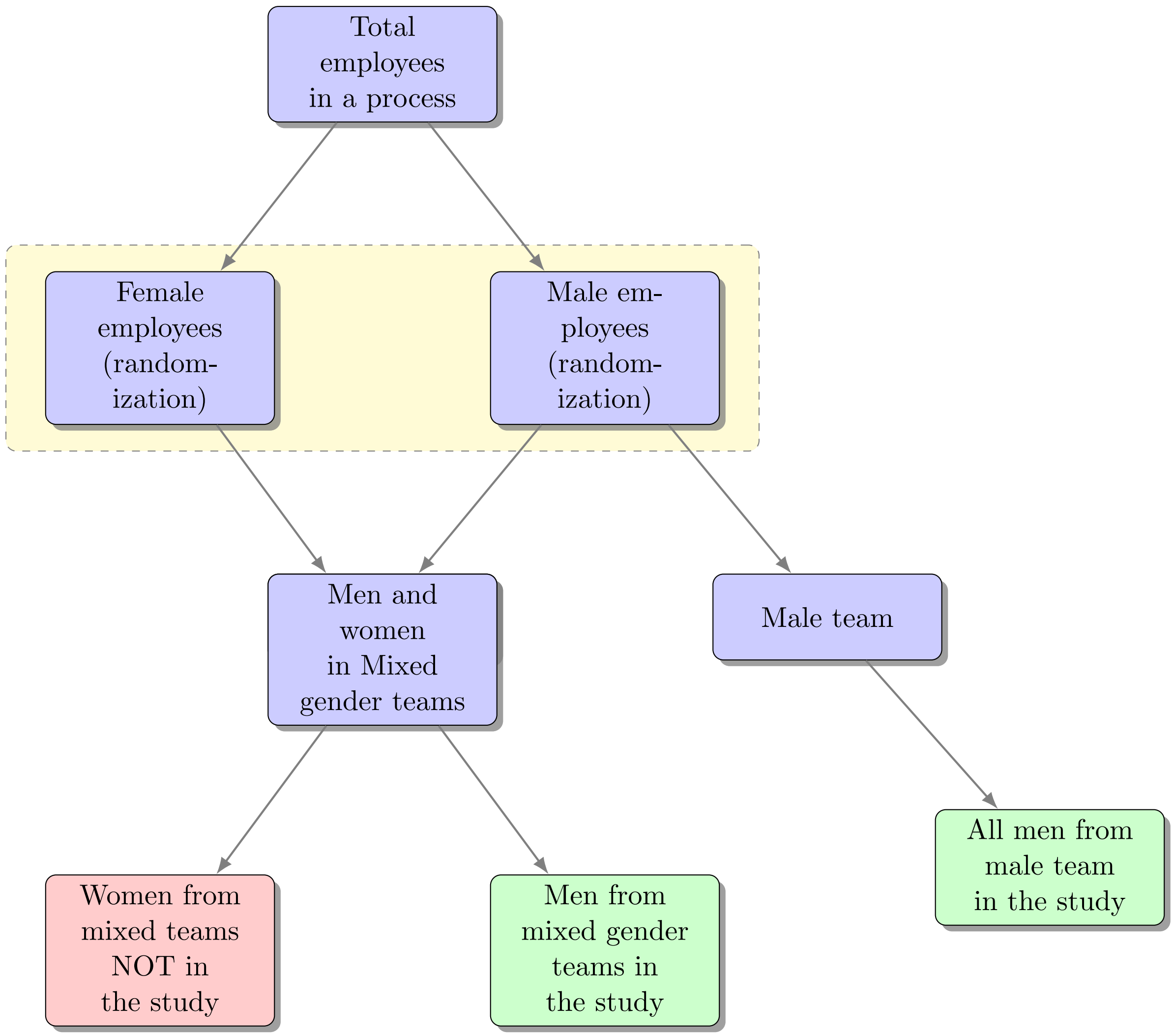
1.6 Figures

Figure 1.1: Randomization design



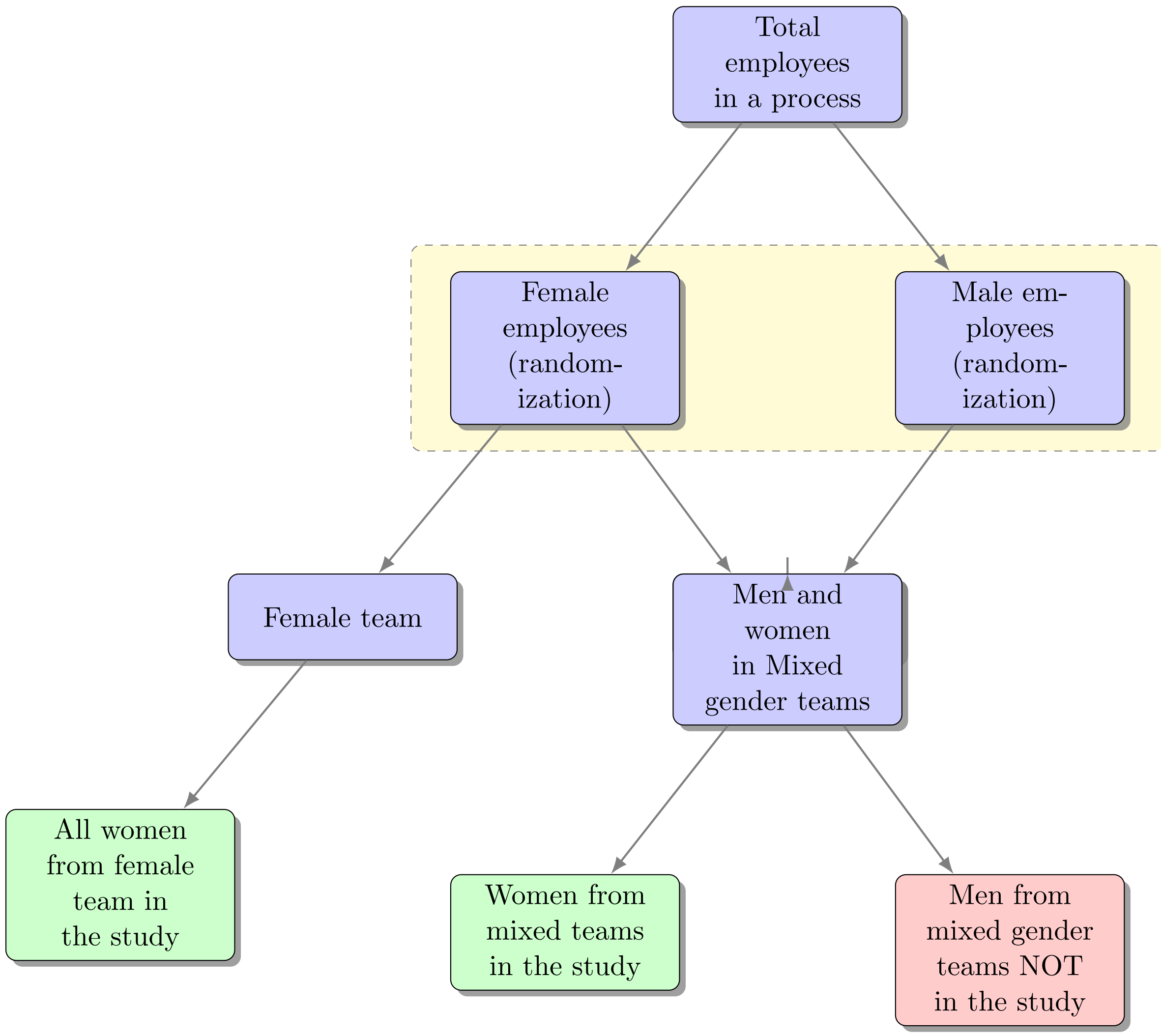
Notes: This is the case for 2 processes in the study. There were approximately equal number of men and women and 4 team leaders to lead the teams. Two mixed gender teams, one all-female and one all-male teams were formed.

Figure 1.2: Randomization design for some cases



Notes: This is the case for 7 processes. There were fewer women so female-only teams couldn't be formed.

Figure 1.3: Randomization design for one case



Notes: This is the case for 1 morning shift process in Udaipur. There were fewer men so male-only teams couldn't be formed.

1.7 Tables

Table 1.1: Pre-intervention Balance

	Male agents			Female agents		
	Mixed team mean/sd	All male team mean/sd	p-value of difference	Mixed team mean/sd	All female team mean/sd	p-value of difference
Age (in years)	21.63	21.77	0.54	22.16	22.36	0.73
	(2.79)	(3.23)		(2.74)	(3.95)	
Education (in years)	13.88	13.66	0.04	14.25	14.16	0.71
	(1.27)	(1.33)		(1.33)	(1.32)	
Attended government school	0.46	0.44	0.69	0.27	0.34	0.35
	(0.50)	(0.50)		(0.48)	(0.45)	
Urban (home place)	0.68	0.69	0.8	0.84	0.81	0.65
	(0.47)	(0.46)		(0.37)	(0.40)	
Experience at the call center (in months)	2.61	2.62	0.98	4.06	2.46	0.27
	(4.76)	(4.61)		(4.55)	(2.67)	
Super index of exposure	0.52	0.51	0.93	0.32	0.27	0.10
	(0.27)	(0.28)		(0.23)	(0.20)	
Past exposure to opposite gender (index)	0.69	0.69	0.86	0.75	0.74	0.6
	(0.18)	(0.18)		(0.15)	(0.16)	
Autonomy (index)	0.73	0.75	0.28	0.74	0.79	0.07
	(0.20)	(0.19)		(0.16)	(0.16)	
Gender attitude (index)	0.57	0.58	0.45	0.51	0.55	0.11
	(0.18)	(0.18)		(0.15)	(0.14)	
Job-satisfaction (index)	2.20	2.34	0.06	2.32	2.55	0.37
	(0.94)	(0.93)		(0.99)	(0.92)	
Number of observations	297	320	617	67	81	148

Notes: This includes the survey responses from male and female agents at the baseline or in the pre-intervention period. For indices such as job satisfaction index, gender attitude index etc., the average response of all the attempted questions for the particular index is calculated. Super index on exposure includes responses for gender attitude, past exposure to opposite gender and average autonomy of females in that process, new batch along with being in north or south Indian process.

Table 1.2: Balance check on baseline productivity

	Male Baseline Productivity (zscore)	*Female Baseline Productivity (zscore)*
Gender integration treatment	.047	-0.11
	(0.09)	(0.13)
Observations	494	91
Control Mean	0	0
Control SD	0.99	0.99
Strata FE	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 This includes the sample of men and sample of women in the study who were randomized at the beginning of the study into the mixed gender (treatment) and same gender teams (control). Out of 617 men, 494 and out of 148 women, 91 of them were from old batches and had past productivity data. They were randomized using the past productivity data at the beginning of the study. The average is taken of the three top productivity variable zscores to get the baseline productivity zscore. Strata fixed effect is included. Standard errors are clustered at the team level.

Table 1.3: Overall impact of gender integration treatment on primary outcomes

	Male agents		Female agents	
	Share of days worked during study period	*Productivity (zscore)*	*Share of days worked during study period*	*Productivity (zscore)*
Gender integration treatment	-0.008	0.017	-0.008	-0.081
	(0.023)	(0.049)	(0.042)	(0.048)
Observations	43,695	20,575	12,227	6,384
Mean	0.49	0	0.56	0
Control SD	0.49	0.98	0.49	0.99
p-value (CGM)	0.76	0.79	0.94	0.33
Date FE	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes
Baseline productivity	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes the sample of males and females in the study who were randomized into the mixed gender (treatment) and all male teams (control) and all female teams (control) in inbound and outbound processes. The primary important productivity variable is the sales and survey made per day in outbound processes and average call handling time in Inbound processes. The secondary productivity variable is ratio of number of surveys by number of calls made in a day in outbound processes and net login hour in Inbound processes. The third productivity variable is the number of calls made per day. All performance measures are z-scores (constructed by taking the average of normalized performance measures, where these are normalizing each individual measure to a mean of 0 and standard deviation of 1). The average is taken of the three productivity variable zscores to get the productivity zscore. The workers were paired up before randomization into treatment and control groups. The regressions are run at the daily level, with strata fixed effects and baseline productivity as a control. Days worked during study period is an indicator variable for whether an employee was present or absent on a date. Standard errors are clustered at the team level, while the p-value reported in the table comes from clustering at the team level using Cameron, Gelbach and Miller's wild-cluster bootstrap.

Table 1.4: Heterogeneous treatment effects on share of days worked during study period

	Male agents		Female agents		
	Low prior exposure	*Regressive gender attitude*	*Low prior exposure*	*Regressive gender attitude*	*Low female autonomy*
Gender integration treatment	-0.003	-0.000	-0.055	-0.014	0.084**
	(0.038)	(0.023)	(0.053)	(0.056)	(0.033)
Treatment*Interaction variable	-0.009	-0.016	0.102	0.010	-0.208***
	(0.047)	(0.046)	(0.078)	(0.080)	(0.040)
Interaction variable	0.004	-0.015	0.029	0.042	-0.144***
	(0.029)	(0.033)	(0.047)	(0.047)	(0.029)
Observations	43,695	43,695	12,227	12,227	12,227
Control Mean	0.494	0.494	0.561	0.561	0.561
Control SD	0.49	0.49	0.49	0.49	0.49
p-value (CGM): Treatment	0.95	0.98	0.47	0.86	0.23
p-value (CGM): Treatment*Interaction	0.87	0.74	0.23	0.90	0.04
p-value (CGM): Interaction	0.89	0.67	0.58	0.45	0.39
Date FE	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
Baseline productivity	No	No	No	No	No

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes the sample of males and females in the study who were randomized into the mixed gender (treatment) and same gender teams (control) in Inbound and Outbound processes. Share of days worked during study period is an indicator variable for whether an employee was present or absent on any particular date within the study period from the day of entering the study. The regressions run at the daily level so controlled for date and strata fixed effects. Standard errors are clustered at the team level, while the p-value reported in the table comes from clustering at the team level using Cameron, Gelbach and Miller's wild-cluster bootstrap.

Table 1.5: Heterogeneous treatment effects on productivity

	Male agents		Female agents		
	Low prior exposure	*Regressive gender attitude*	*Low prior exposure*	*Regressive gender attitude*	*Low female autonomy*
Gender integration treatment	-0.023	0.105	-0.030	-0.062	-0.012
	(0.074)	(0.069)	(0.128)	(0.080)	(0.087)
Treatment*Interaction variable	0.079	-0.192**	-0.114	-0.053	-0.128
	(0.096)	(0.088)	(0.236)	(0.239)	(0.090)
Interaction variable	-0.114*	0.058	-0.011	-0.101	-0.706***
	(0.065)	(0.062)	(0.210)	(0.123)	(0.149)
Observations	20,575	20,575	6,384	6,384	6,384
Control Mean	0	0	0	0	0
Control SD	0.98	0.98	0.99	0.99	0.99
p-value (CGM): Treatment	0.81	0.19	0.86	0.6	0.89
p-value (CGM): Treatment*Interaction	0.42	0.05	0.63	0.82	0.34
p-value (CGM): Interaction	0.11	0.32	0.91	0.46	0.58
Date FE	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
Baseline productivity	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes the sample of males and females in the study who were randomized into the mixed gender (treatment) and same gender teams (control) in Inbound and Outbound processes. The primary important productivity variable is the sales and survey made per day in Outbound processes and Average call handling time in Inbound processes. The secondary productivity variable is ratio of number of surveys by number of calls made in a day in Outbound processes and net login hour in Inbound processes. The third productivity variable is the number of calls made per day. All performance measures are z-scores (constructed by taking the average of normalized performance measures, where these are normalizing each individual measure to a mean of 0 and standard deviation of 1). The average is taken of the three productivity variable zscores to get the productivity zscore. The workers were paired up before randomization into treatment and control groups. The regressions are run at the daily level, with strata fixed effects and baseline productivity as a control. Standard errors are clustered at the team level, while the p-value reported in the table comes from clustering at the team level using Cameron, Gelbach and Miller's wild-cluster bootstrap.

Table 1.6: Overall impact of gender integration treatment on secondary outcomes for males

	Gender attitude index (zscore)	*Job satisfaction index (zscore)*	*Knowledge sharing index (zscore)*	*Dating*	*Peer monitoring and support index (zscore)*	*Comfort with opposite gender*
Gender integration treatment	-0.19	-0.01	0.31**	0.19**	0.05	0.05**
	(0.20)	(0.17)	(0.14)	(0.06)	(0.17)	(0.02)
Observations	327	327	327	234	327	327
Control Mean	0	0	0	0.54	0	0.32
Control SD	0.99	0.49	0.99	0.5	0.99	0.99
p-value (CGM)	0.42	0.97	0.04	0.02	0.77	0.03
Date FE	No	No	No	No	No	No
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline control	Yes	Yes	Yes	Yes	Yes	No

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes the sample of males in the study who were randomized into the mixed gender (treatment) and all male teams (control) for which endline data was collected for the entire process. The knowledge sharing index is calculated using the average of two survey responses on whether the person sitting nearby affects the employee's productivity and whether the employee talked to agents sitting nearby about how to improve work for more than 5 minutes daily on average. Peer monitoring and support index includes survey responses on questions on comfort and monitoring in the team and support of team members. Dating is an indicator variable that uses survey response on whether the employees are currently dating someone (but not married). Comfort with opposite gender is an indicator variable on survey response on whether the employees are comfortable receiving feedback infront of opposite gender. The average is taken of the survey responses on questions on gender attitude to form an index. A progressive answer was coded as 1 and regressive answer was coded as 0. Job satisfaction is an index of survey response on three questions on emotional exhaustion during work life. These indices were normalized using control group mean and standard deviations within processes to form z-scores. The workers were paired up before randomization into treatment and control groups. The regressions are run at individual level for the processes for which endline is available, with strata fixed effects and baseline control. Standard errors are clustered at the team level, while the p-value reported in the table comes from clustering at the team level using Cameron, Gelbach and Miller's wild-cluster bootstrap.

Table 1.7: Overall impact of gender integration treatment on secondary outcomes for females

	Gender attitude index (zscore)	*Job satisfaction index (zscore)*	*Knowledge sharing index (zscore)*	*Dating*	*Peer monitoring and support index (zscore)*	*Comfort with opposite gender*
Gender integration treatment	0.25	0.27	-0.11	0.01	0.22***	0.06
	(0.14)	(0.17)	(0.14)	(0.16)	(0.04)	(0.13)
Observations	146	146	146	92	146	146
Control Mean	0	0	0	0.62	0	0.55
Control SD	0.99	0.49	0.99	0.5	0.99	0.99
p-value (CGM)	0.18	0.22	0.5	0.95	0.00	0.82
Date FE	No	No	No	No	No	No
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline control	Yes	Yes	Yes	Yes	Yes	No

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes the sample of all females in the study who were randomized into the mixed gender (treatment) and all female teams (control). The knowledge sharing index is calculated using the average of two survey responses on whether the person sitting nearby affects the employee's productivity and whether the employee talked to agents sitting nearby about how to improve work for more than 5 minutes daily on average. Peer monitoring and support index includes survey responses on questions on comfort and monitoring in the team and support of team members. Dating is an indicator variable that uses survey response on whether the employees are currently dating someone (but not married). Comfort with opposite gender is an indicator variable on survey response on whether the employees are comfortable receiving feedback infront of opposite gender. The average is taken of the survey responses on questions on gender attitude to form an index. A progressive answer was coded as 1 and regressive answer was coded as 0. Job satisfaction is an index of survey response on three questions on emotional exhaustion during work life. These indices were normalized using control group mean and standard deviations within processes to form z-scores. The workers were paired up before randomization into treatment and control groups. The regressions are run at individual level for the processes for which endline is available, with strata fixed effects and baseline control. Standard errors are clustered at the team level, while the p-value reported in the table comes from clustering at the team level using Cameron, Gelbach and Miller's wild-cluster bootstrap.

1.8 Appendix

Table 1.8: Selective attrition balance check on individual characteristics

	(1) Mixed team mean/sd	(2) All male team mean/sd	(3) t-statistic of difference
Age (in years)	21.88	21.74	-0.53
	(2.95)	(3.10)	
Education (in years)	13.88	13.63	-2.25
	(1.30)	(1.31)	
Attended government school	0.44	0.48	0.90
	(0.50)	(0.50)	
Urban (home place)	0.65	0.65	-0.07
	(0.48)	(0.48)	
Agent's work experience (number of months)	2.27	2.98	1.19
	(4.01)	(5.22)	
Ever been unemployed	0.40	0.45	1.07
	(0.49)	(0.50)	
Past exposure to opposite gender (index)	0.69	0.70	0.50
	0.19	0.18	
Autonomy (index)	0.73	0.75	0.90
	(0.20)	(0.19)	
Gender attitude (index)	0.57	0.57	0.13
	(0.19)	(0.18)	
Peer pressure (index)	3.12	3.16	0.43
	(1.05)	(1.05)	
Stress level (index)	1.94	2.03	1.02
	(1.05)	(0.97)	
Self-esteem (index)	(0.37)	(0.36)	-0.21
	(0.28)	(0.30)	
Job-satisfaction (index)	2.23	2.34	1.37
	(0.97)	(0.92)	
Observations	252	290	542

Notes: This includes the survey responses from male agents at the baseline or in the pre-intervention period. For indices such as job satisfaction index, gender attitude index etc., the average response of all the attempted questions for the particular index is calculated.

Table 1.9: Effect of gender integration on primary outcomes for processes

	Male agents		Female agents	
	Share of days worked during study period	*Productivity (zscore)*	*Share of days worked during study period*	*Productivity (zscore)*
Gender integration treatment	0.003	-0.030	-0.008	-0.081
	(0.019)	(0.073)	(0.042)	(0.048)
Observations	35,058	12,409	12,227	6,384
Mean	0.36	0	0.56	0
Control SD	0.48	0.97	0.49	0.97
Date FE	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes
Baseline productivity	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1 This includes the sample of males and females in the study who were randomized into the mixed gender (treatment) and all male teams (control) and all female teams (control) in Inbound and Outbound processes for processes with full endline data available. For males, endline data is available for 5 out of the 9 processes. For female endline data is available for all 3 processes. The primary important productivity variable is the sales and survey made per day in Outbound processes and Average call handling time in Inbound processes. The secondary productivity variable is ratio of number of surveys by number of calls made in a day in Outbound processes and net login hour in Inbound processes. The third productivity variable is the number of calls made per day. All performance measures are z-scores (constructed by taking the average of normalized performance measures, where these are normalizing each individual measure to a mean of 0 and standard deviation of 1). The average is taken of the three productivity variable zscores to get the productivity zscore. The workers were paired up before randomization into treatment and control groups. The regressions are run at the daily level, with strata fixed effects and baseline productivity as a control. Days worked during study period is an indicator variable for whether an employee was present or absent on a date. Standard errors are clustered at the team level.

Survey Questions

Past exposure to opposite gender index : It constitutes of answers from the following Agree/Disagree questions

1) Did you go to a co-educational school?

2) If co-ed, did boys and girls sit together?

3) Do you have opposite gender siblings?

4) Did you grow up in a joint family with any opposite gender cousins?

5) Did you have a female teacher in school?

6) Did you have any friends from your neighborhood who were from the opposite gender?

7) Have you ever been in a relationship?

8) Have you ever had a team leader of opposite gender?

9) Does your mother or female family members practice ghoonghat/burqa?

10) Do you have lunch with opposite gender?

Job Satisfaction index – rank on a scale of 1 to 5

1) I feel used up at the end of the work day

2) I dread getting up in the morning and having to face another day on the job.

3) I feel I am working too hard on my job.

Gender attitudes index- The response for each of the following questions was aggregated to form an index of gender attitude. Each response was coded as 1 if the respondent answered "Strongly Agree" or "Agree" with a gender-progressive statement or "Strongly Disagree" or "Disagree" with a gender-regressive statement, and 0 otherwise. The following questions are based on gender attitude questions in Dhar et al., 2018, Glennerster et al. (2018) and some new questions specific to the setting, designed by the author.

Express if you agree or disagree with the following statements:

Education attitudes

1) Wives should be less educated than their husbands

2) I want my spouse to be more educated than me

3) Boys should be allowed to get more opportunities and resources for education than girls

I. Employment attitudes

1) I wouldn't let my sister work in a call center as it is not a suitable job for women from good families.

2) I want my spouse/partner to earn more than me

3) A woman's most important role is to take care of her home, feeding kids and cook for her family

4) Men are better suited than women to work outside of the house

5) Marriage is more important for a woman than her job

7) Men are the best at leading at the highest level

8) Men should take care of the house if they earn less

9) I will not allow my sister to have a boyfriend before marriage

II. Women's role attitudes

1) Nowadays men should participate in child rearing and household chores rather than leaving it all to the women.

2) Brothers should monitor their sister's friends and her phone as it is their responsibility

3) Sisters should monitor their brother's friends and his phone as it is their responsibility

4) Daughters should have a similar right to inherited property as sons

5) Women should dress up according to what her husband or family allows for the sake of her family honor

6) A man should have the final word about decisions in his home

7) A woman should tolerate violence in order to keep her family together

8) Parents should maintain stricter control over their daughters than their sons

9) A shy demeanour makes a girl a more suitable bride

10) A woman has to have a husband or sons or some other male kinsman to protect her.

11) I won't allow my sister to go to college if it is in the city far away from home

12) Having a son is important to me because it will make my parents and in-laws satisfied.

III. Fertility attitudes – marked as gender regressive if answers to the first fertility question is

A and if the reply is answer C in question 1 and but answer B in question 2.

1) Suppose the first two children born to a husband and wife are both girls. Which of the following should they do?

(A) have more children till they have a boy child

(B) no more children, as this is the perfect family size

(C) have one more child but no more

2) Suppose the first two children born to a husband and wife are both boys. Which of the following should they do?

(A) have more children

(B) no more children

(C) have one more child but no more

Peer monitoring and support

1) Do your teammates monitor your work?

2) Do you feel that your teammates are interested in your performance?

3) Do your teammates offer suggestions for performance improvement?

4) Do you feel comfortable in the workplace?

5) Do you feel comfortable with your teammates?

Autonomy

Index of number of decisions that individual is the most important decision-maker for (they answer respondent is most important) among following decisions:

1)Clothes for yourself

2) Whether you work outside the home

3) How money earned by you is spent

4) Time you spend socializing outside the house

5) What education/training pursuits you follow

6) Selection of a spouse for you

7) With whom do you travel to work

Chapter 2

Impact of Air Pollution on Employee Productivity: Evidence from Indian Call Centers

Abstract

We study the effect of pollution on both extensive and intensive margins of productivity, using high quality individual-level daily productivity data from call centers in five Indian cities. Fine particulate matter ($PM_{2.5}$), which easily permeates indoors, has the potential to impact an individual's short-run productivity. We focus on the effect of pollution above 35.4 $\mu g/m^3$ $PM_{2.5}$, which is viewed as harmful according to both WHO and EPA guidelines. On days in which pollution is above this threshold, average productivity decreases by 0.19 standard deviations. We further explore changes in productivity by whether a call center team works in an inbound process that receives customer support calls or an outbound processes that makes sales calls. There is a 0.12 SD reduction in productivity for inbound processes, with a 6.7% reduction in calls answered on high pollution days. In outbound processes productivity is reduced by 0.4 SD, which corresponds with an efficiency loss of 14.6% as measured by sales per call. We also find a precisely estimated zero effect on attendance on high pollution days.

2.1 Introduction

Causing seven million premature deaths every year globally, air pollution has been a growing concern all over the world (WHO, 2017).[1] With six out of the ten most polluted cities in the world in India, it has been a particularly pressing issue in India (WHO databse, 2018).[2] Therefore, understanding the impact of pollution on the economy, especially in developing countries such as India is crucial. This paper studies the impact of daily fluctuations in air quality on employee productivity in call centers in five Indian cities.

The paper focuses on particulate matter concentrations measuring up to 2.5 microns in size. This is because this pollutant can penetrate indoors and building shells cannot provide filtration of these airborne particles present in ambient air (Thatcher and Layton 1995). These fine particulate matters cause serious health issues by impairing cardiovascular and lung functioning (Liu et al., 2017), or can cause daily allergies resulting in nose and throat irritation and mild headaches (Bernstein et al., 2008; Ghio et al. 2000). So, $PM_{2.5}$ can potentially hamper an individual's productivity both at the intensive and extensive margins.

We use a daily panel of productivity data from two call centers located in five Indian cities for a period of 4 to 16 weeks, to study productivity at both intensive and extensive margins. The key identifying variation is the daily fluctuation in air quality ($PM_{2.5}$ levels), which is potentially unrelated to firm's output. This is because these firms don't contribute to the pollution levels directly. The objective of the study is to test whether high or low pollution decreases productivity, by using the WHO and EPA cut off of acceptable $PM_{2.5}$ levels of 35.4 $\mu g/m^3$. Our preferred specification includes both date and worker fixed effects. The date fixed effects address the concerns of bias from unobservables that change over time but are constant over workers, such as the server

[1] In addition, latest research provides evidence that long-term exposure to fine particulate matter ($PM_{2.5}$) is linked to an increased risk of COVID-19 death (Wu et al., 2020; Conticini et al., 2020).

[2] WHO database `https://www.who.int/airpollution/data/en/` (Accessed in May, 2020)

being down or higher traffic on the road. And the worker fixed effect controls for factors that differ across workers but are constant over time, such as age, gender and education of workers.

On the intensive margin, pollution can cause decreases in efficiency and productivity due to allergies, irritation etc. On the extensive margin, there is a theoretically ambiguous impact of pollution on days or hours worked. On one hand, there could be a reduction in days worked or hours worked due to pollution caused illness of the worker or her family member. On the other hand, there could be an increase in work hours or days worked on more polluted days if the worker values leisure more on better health days. In this case, the worker will substitute away from work on less polluted days compared to more polluted days. In both intensive and extensive margins of productivity, there is a possibility that there will be no impact of pollution if individuals are practicing mitigating behaviors on high pollution days. However, this is difficult to follow for an individual in a work setting, unless a firm level policy change such as installation of air purifier is made and no such changes were made in the call center policies during the study period.

We find an effect of 0.19 standard deviation reduction in overall productivity on high pollution days (above 35.4 µg/m ^{3} $PM_{2.5}$), compared to that on low pollution days. This is statistically significant at the 1% level (Table 3). The productivity measures vary by the two kinds of voice support business contracts or processes that the call centers offer. Inbound processes receive incoming calls and outbound processes make outgoing sales calls. So, the productivity index is disaggregated by the type of process for further exploration. We expect the impacts to be different in the two kinds of processes because outbound or sales calls usually have higher pressure, heavier monitoring and tougher targets. Therefore, it is expected that there will be a higher impact of pollution on productivity in outbound processes than inbound ones, if the mechanism is cognitive impairment.

The inbound processes provide customer support services to incoming callers, so their main productivity measures are average call handling time (ACHT), number of calls and net login hours. The firm profits increase if the workers receive a high number of calls, login successfully for at least 8 hours and handle the calls in less amount of time. We find an overall 0.12 SD significant decline in productivity on high pollution days for inbound processes (Table 3). This effect is driven by decreases in calls answered by 6.7% compared to the average calls answered on low pollution days (Table 4).

The main productivity variables in outbound processes are total sales made per day, total calls made per day and their ratio of total sales by calls made per day. The firm gains profits if total sales made per day increases and if the ratio of sales by calls also increases per day. So, the firms benefit if an employee has a high sales conversion rate of calls, that is, the employee achieves daily sales targets by making fewer number of calls. Less total number of calls made per day in the outbound processes is therefore better for the firm. For outbound processes, the overall effect on productivity is 0.4 SD compared to that on low pollution days (Table 3). This effect is largely driven by a reduction in sales by 30% over the mean sales of 54.3 on low pollution days (Table 5). We also find a significant decline in the efficiency measure of sales by calls ratio per day. This amounts to an efficiency loss of 14.6% in the sales by calls ratio per day on high pollution days (Table 5).

Absenteeism is a particularly important issue in the context of India. In fact in the period between 1999 and 2013, Indian firms lost an average of 8.7% scheduled worker-days due to the absence of permanent workers (Krishnaswamy, 2019). In this paper we find precisely estimated zero effect of high pollution on attendance (Table 2). So, pollution maybe not be one of the reasons driving the high absenteeism rates in this industry in India. In addition, the zero effect on attendance mitigates concerns about selection effect on the intensive margins of productivity.

This paper adds to the literature on air pollution and productivity that uses high frequency employee-level data. There has been a focus on productivity in physically demanding occupations such as agricultural workers (Graff Zivin and Neidell, 2012), pear-packing factory workers (Chang et al., 2014), garment factory workers (Adhvaryu et al., 2016), textile assembly (He et al., 2019) and manufacturing firms (Fu et al., 2017; Hansen-Lewis, 2018). These papers generally find negative impact of pollution on worker productivity.

Modern and developing economies such as India rely on the service sector for their economic output and economic growth. These high-skilled jobs require mental strength and not physical strength. This paper makes a direct contribution to the small and growing literature on air pollution and productivity in cognitively demanding tasks. There are papers study cognitively demanding jobs such as decisions made by baseball umpires (Archsmith et al., 2018) and investor behavior (Heyes et al., 2016). But our paper is most closely related to the study by Chang et al. (2019), which studies the impact of pollution on productivity in Chinese call centers. Our study builds on that paper by using $PM_{2.5}$, instead of PM_{10}, a measure that captures smaller particulates, which are especially likely to permeate indoors. In addition, we are able to study outbound processes that require extra cognitive demands, as well as inbound processes. Finally, we have access to data that focuses on call-level efficiency measures of productivity.

Assessing the impact of pollution on productivity has broad policy implications by making a concrete case for stronger environment protection laws, particularly in developing countries. These developing economies are going through urbanization and economic growth and are therefore, not receptive to changes in environmental policies which might deter growth. However, evidence of a causal relationship between air pollution and productivity can convince countries to take stringent measures to protect the environment.

2.2 Context

This section provides an overview on the ill-effects of air pollution on health and some details about the call center industry in India. The first subsection provides information about the air quality index, particulate matter and a background on pollution. The second subsection provides information about the call center setting of this study.

2.2.1 Background on Pollution

Air pollution is an environmental risk to human health. Air pollution is a mixture of particulate matter (PM), ozone, carbon monoxide, sulfur oxides, nitrogen oxides, methane, and other gases, volatile organic compounds, and metals such as lead and iron. We focus on fine particulate matter ($PM_{2.5}$) in this study because it can penetrate indoors and cause harmful short-run effects on health. "Small particles" are inhalable coarse particles with a diameter of 2.5 to 10 µg/m ^{3} and "fine particles" are smaller than 2.5 µg/m ^{3} in diameter. Therefore, $PM_{2.5}$ are fine particulate matter with an aerodynamic diameter of 2.5 m or less ($PM_{2.5}$). Fine particulate matters are anthropogenic emissions from fuel combustion, engine exhaust and high temperature industrial processes (Dickey, 2000). Particulate matter exposure acts as the source of various health problems such as premature death in individuals suffering from heart or lung disease, non-fatal heart attacks, irregular heartbeat, aggravated asthma, decreased lung function, and increased respiratory symptoms such as irritation of the airways, coughing, or difficulty breathing (Kim et al., 2015).

While the epidemiological and toxicological literature have provided evidence on the long-term morbidity and mortality effects of $PM_{2.5}$ through impairment of the respiratory and cardiovascular systems, there is also a growing literature on the short-run effect of fine particulate matter both on health and cognition (Bell et al., 2008; Pascal et al, 2014). PM is small enough to penetrate the lung barrier, enter the bloodstream and travel into the central nervous system (Elder et a., 2015). The potential mechanism through which inhaled indoor pollution impairs brain function is through neuroinflammation (Brockmeyer and D'Angiulli, 2016). Therefore, greater exposure to fine particles is associated with cognitive problems affecting intelligence, mood disorders and performance (Allen et al., 2017; Tallon et al., 2017). Since our call center or office setting, requires concentration and critical thinking, a well-functioning brain is critical to achieving higher productivity (Chang et al, 2019).

According to the National Ambient Air Quality Standards for Particle Pollution (U.S. Environmental Protection Agency (EPA)), 24-hour averages of $PM_{2.5}$ levels above 35.5 µg/m^3 is unhealthy for sensitive groups. $PM_{2.5}$ levels above 55.5 µg/m^3 is unhealthy and that above 150.5 µg/m^3 is deemed extremely unhealthy for the general population.[3] The five cities of Mumbai, Noida, Patna, Udaipur and Hubli included in the study, experience very high levels of pollution and some of these cities have also experienced hazardous levels of $PM_{2.5}$ with daily averages even above 250.5 µg/m^3.

India has taken some steps to address the growing concerns about pollution in the country. At the beginning of 2019, the Ministry of Environment, Forest and Climate Change, Government of India announced the National Clean Air Programme (NCAP) to provide a national framework for air quality management. A total of 122 cities in India have been identified as 'non-attainment cities' for not meeting air quality standards for particulate matter. There are 207 realtime air monitoring stations spread across 114 cities, and 793 manual air monitoring stations spread across 344 cities in India. Under NCAP, massive investments are being made to further expand real-time and manual air monitoring stations, particularly in non-attainment cities (Roychowdhury and Somvanshi, 2020). Out of the cities in our study, Patna and Noida are included in the 30 most polluted cities in the world and Mumbai and Udaipur are included the 100 most polluted cities (WHO databse, 2018).[4]). This study aims to provide additional evidence on the economic impact of pollution to further inform policy makers.

2.2.2 Background on Call Centers in the study

The call center industry in India is the largest private sector employer in India. We collected data from two call centers in India: Call-2-Connect India Pvt. Ltd. and Five Splash

[3]Revised Air Quality Standards for Particulate Pollution and Updates to Air Quality Index (AQI) `https://www.epa.gov/sites/production/files/2016-04/documents/2012_aqi_factsheet.pdf` (accessed in May, 2020)

[4]WHO database `https://www.who.int/airpollution/data/en/` (Accessed in May, 2020)

Infotech Pvt. Ltd. Call2Connect India Pvt. Ltd. has centers located in the states of Bihar (Patna), Uttar Pradesh (Noida) and Maharashtra (Mumbai). Five Splash Infotech Pvt. Ltd. has centers in the states of Rajasthan (Udaipur) and Karnataka (Hubli).

Calls centers are also known as Business Process Outsourcing (BPO) companies. They provide voice and non-voice support to other companies. A call center can have contracts with various companies and each of these contracts is called a process. The nine processes in our study provide voice support in the form of either inbound or outbound calls. Entry-level workers, also known as agents provide the voice support. Agents work in teams of 20-25 and are supervised by team leaders.

We analyze productivity data for the agents because the firms profits rely on their work. Call centers usually run all seven days in a week. However, the agents work six days a week and can choose any day of the week as a day off. The agents in our sample receive a fixed salary of $100-150 per month in smaller cities and $150-220 per month in the bigger cities. Since attendance is a major issue in India, agents receive a deduction in their salary if they take too many holidays in a month. If an agent doesn't show up to work for 3-4 days in a row without informing their team leaders, they are marked as absconding in the attendance sheet. The agents have a difficult time re-joining work if they were absconding. Additionally, if an agent takes too many holidays (varies for different centers) in a month even after informing their team leaders about it, they receive a deduction in their salary.

Employees are expected to be logged-in for a certain number of hours so even if they come late to work, they are expected to complete their log-in hours. Agents are also penalized for coming late for work. If they come late to work 3-4 days a week, they face a salary deduction.

In inbound processes, agents receive calls and offer customer service support to customers. The inbound processes in our study provide help to all kinds of companies such as food delivery, financial technology, beauty retail etc. In outbound processes, agents usually make calls to make sales. In our sample, outbound calls are made during elections by a political party as part of their campaign/advertisement to provide campaign information to eligible voters.

2.3 Data

We have five inbound and four outbound processes in our study. The agents are required to log-in to the system as soon as they show up for work. Their productivity data is recorded automatically using technology-based monitoring system. We use this internally collected administrative data for 4 to 16 weeks from all of the five cities/locations.

The inbound processes provide customer support services to incoming callers, so their main productivity measures are average call handling time (ACHT), number of calls and net login hours. The firms gain profits if the workers receive a high number of calls, login successfully for at least 8 hours and handle the calls in less amount of time.

In outbound processes in which agents make sales calls, the primary productivity variables are total sales made per day, total calls made per day and their ratio of total sales by calls made per day. The firms gain profits if total sales made per day increases and if the ratio of sales by calls also increases per day. So, the firms benefit if an employee has a high sales conversion rate of calls i.e., she achieves daily sales targets by making fewer number of calls.

The main outcome measure at the extensive margin is days present in the study period. In the daily level administrative productivity data, there is information on the productivity of all the logged-in workers on any particular date. This gives information on who was present and absent on each particular day of the study from the first day of appearing in the administrative data to their last day. Using this, each worker is marked to be present on the days in the study for which their productivity data is available till their last date of appearing in the data. For other days in between, they are marked absent if their productivity data is missing.

For the daily-level data on pollution, India Central Pollution Control Board Data was requested for data.[5] National Oceanic and Atmospheric Administration (NOAA) was requested for information on daily average temperature. The daily average temperature data was unavailable for Udaipur and Hubli at NOAA data-base. So, the temperature data for the nearest city for which this information was available is used as a proxy.

Table 1 provides some sample statistics on pollution in the various cities in the sample during the study period. Noida is the most polluted city in the sample with average $PM_{2.5}$ levels of 150.33 The second most polluted city is Patna with average $PM_{2.5}$ of approximately 53. Udaipur and Mumbai follow behind Patna with average $PM_{2.5}$ levels of 37.21 and 34.29. Hubli is the least polluted city in the sample with average $PM_{2.5}$ levels as 25, which is under the WHO and EPA acceptable air quality standard of 35.4. The minimum $PM_{2.5}$ levels in the study-period in all these cities is below 35.4.

In Table 1, we also provide sample statistics of the productivity measures both at the extensive and intensive margins. The average attendance is about 77% in the full sample. For inbound processes, where agents answer calls as customer service support, the average call handling time is approximately 900 seconds. The workers log-in for an average of 7.9 hours and they answer 122 calls per day on average. In outbound processes, the agents make an average of 65 sales per day by making 180 calls on average in a day. So, the average sales per calls ratio is around 0.37. The standard deviation for all these measures is quite high. The next sections provides details about the empirical strategy.

2.4 Empirical Specification

We use this panel data for workers in call centers across five Indian cities to estimate the effect of pollution on productivity. The estimating equation is as follows:

[5] CPCB - India Central Pollution Control Board : `cpcb.nic.in/` (accessed in April, 2020)

$$Y_{ipjt} = \beta_0 + \beta_1 \text{HighPM}_{2.5jt} + \beta_2 \text{AverageTemperature}_{jt} + \beta_3 \text{Process}_p + X_i + \upsilon_t + \epsilon_{ipjt} \quad (2.1)$$

The dependent variable in productivity for individual 'i' in process 'p', at city 'j' on date 't'. Air quality or air pollution is the presence of particle matter 2.5. High $PM_{2.5}$ levels is $PM_{2.5}$ above 35.4 which is deemed unhealthy by both WHO and EPA air quality standards. Productivity variables are standardized within a process using pollution level ($PM_{2.5}$) less than 35.4 level as control. We first standardize each measure of intensive margin of productivity within a process using mean and standard deviation of the acceptable pollution group. We then add these measures and re-standardize the to create a z-score of productivity.

We add temperature controls because some of the daily variation in productivity could be due to daily temperature fluctuations. Date fixed effects are included in the regression analysis to control for unobserved heterogeneity within date/time. These date fixed effect addresses the concerns of bias from unobservables that change over time but are constant over workers, such as server being down or days with higher traffic on the road. We also control for worker fixed effect in some specifications to account for time-invariant unobserved within-worker heterogeneity, such as age, gender and education of workers. Process-level fixed effects account for unobserved variations in productivity within a business. These are included in those specifications where worker fixed effects are not included. When worker fixed effects are included, Process fixed effects have to be dropped because of collinearity. Because the error term likely exhibits autocorrelation between observations within a city on a particular date, we cluster at the city date level.

A potential threat to identification is that pollution and productivity are correlated through the channel of increasing economic activity in an area. These call centers don't contribute to the pollution levels directly. However, they could potentially be working for processes which have higher call volumes and higher work burden on days with high pollution. Since most of these processes are dealing with local callers/ customers from an entire state, it is unlikely to be related to the pollution in the city in which the call center office is located. For outbound calls, these calls took place for a few months prior to state elections. So, they are likely related to the pollution in the city if the ruling party in the state expedited the construction work in that area just before the elections. However, even in this case, the call center office was located in the suburban area which lies out of the state with eligible voters. Additionally, the lists of calls to be made to customers is provided to the call centers by process owners a few days or weeks in advance. Therefore, the demand for call center's services is assumed to be unrelated to daily pollution. So, any links to number of callers and daily fluctuations in pollution is improbable.

2.5 Regression Results

In this section we layout the regression results disaggregated by margin of productivity. We further disaggregate the intensive margin of productivity by process and individual productivity measures. Additionally, we report the results from some robustness checks.

2.5.1 Main Regression Results for the Extensive Margin of Productivity

In Table 2, we provide the regression results for the extensive margin of productivity, attendance for the full sample as well disaggregation by the type of process. We find a precisely estimated zero effect of unhealthy air pollution levels on attendance for all the cases. There is a 0.008 increase (or 1% increase) in attendance on high pollution days, which is a small and insignificant effect, with tight confidence interval around zero [CI: -0.012 to 0.0276]. When we add worker fixed effects, the point-estimate reduces further to 0.002 (column 2), which is an effect of 0.26% increase in attendance over mean attendance of 0.77. This is also a null-effect with tight confidence intervals around zero [CI: -0.016 to 0.02].

For inbound processes (column 3 of Table 2), we find the same null effect on attendance with a small and insignificant point-estimate of 0.002 [CI: -0.023 to 0.0277]. When we add worker fixed effect, the point-estimate remain small and insignificant, but the sign or direction of change becomes negative. There is a -0.003 change in attendance (column 4 of Table 2), which is a 0.4% decrease in attendance on high pollution days over the mean attendance in inbound processes of 0.74. This is a null effect because the standard errors are small and the point-estimate lies in tight confidence intervals containing zero [CI: -0.025, 0.019].

The outbound processes have a higher average attendance of 0.81. The impact of high air pollution on attendance in outbound processes is 0.027, which is a 3.3% increase in attendance (column 5 of Table 2). However, this is also a small and insignificant effect which is statistically indistinguishable from zero [CI: -0.016 to 0.07]. The last column of Table 2 provides evidence on the impact of high particulate matter in the air on attendance in outbound processes with worker fixed effects. We again find a null effect with a point-estimate of 0.015 [CI: -0.026, 0.056].

The null-effect on attendance is expected because of the stringent attendance policy followed by call centers, as discussed in section II (D'Cruz and Noronha, 2013). However, despite these policies, absenteeism is an important issue in India (Krishnaswamy, 2019). Our analysis provides evidence that air pollution is not one of the reasons causing high absenteeism, particularly in the BPO industry. These results also imply that our estimates on the effect of pollution on intensive margins of productivity presented in the next sub-section are not affected by sample-selection bias.

2.5.2 Main Regression Results for the Intensive Margin of Productivity

In Table 3, we report the results on the intensive margins of productivity for both inbound and outbound processes. We find an overall 0.19 standard deviation reduction in productivity on high pollution days compared to that on the low pollution days. This effect is significant at the 1% level over the full sample both with and without worker fixed effects (see columns 1 and 2). These estimates lie in tight confidence intervals excluding the null-value [CI: -0.323 to -0.063].

We also report the productivity index results by the type of process. For inbound processes, we find an effect of 0.12 SD decrease in productivity on high pollution days compared to that on low pollution days. This is again a statistically significant effect at 1% level. For outbound processes, we find a larger effect of 0.46 SD decrease in productivity due to high pollution (see column 5 of Table 3). These effects are significant at 5% level, due to comparatively larger standard errors than those for inbound processes. But the confidence intervals still exclude the null value [CI: -0.07, 0.85]. When we add worker fixed effects, we find that the effect reduces a little to 0.42 SD and are significant at 5% level (see column 6 of Table 3). Overall, the coefficients in Table 3 remain largely unchanged by the addition of worker-specific fixed effect.

We report each individual component of the standardized index for both inbound and outbound processes (columns 5 and 6 in Table 3). For inbound processes, as discussion in section III, a lower average call handling time (ACHT) is better so that workers can cater to more number of customers. We find an increase in average call handling time by 75.85 seconds, which is a 9.7% increase over the mean ACHT of 784.5 on low pollution days (column 1 of Table 4). This effect is not significant and the standard errors are quite large. Additionally, the effect further diminishes to 5.4% with a point estimate of 42.05, when we add worker fixed effect (column 2 or Table 4). However, the positive sign on ACHT indicates that air pollution might be decreasing worker efficiency, even though this is a small and insignificant effect.

The other two measures of productivity for inbound processes are logged-in hours and calls answered. There is evidence of a significant increase in hours login hours on high pollution days. The point-estimate is 0.31, which is a 4% increase in login hours over the mean login hours of 7.7 on low pollution days (column 3 of Table 4). However, this effect decreases with worker fixed effect to a point estimate of 0.24, which is still significant at the 10% level (column 4 of Table 4). Call centers often ask their workers to remain logged-in for a longer time on days that their efficiency is low because of the real-time monitoring facility. In addition, the call centers gain profits if workers answer a high number of calls per day. We provide evidence that the calls answered declines by 6.7% on high pollution days, compared to the mean of 111.7 on low pollution days. The point-estimate of 7.4 doesn't change much with worker fixed effect (see columns 5 and 6 of Table 4). This is significant at the 5% level.

In Table 5, we report the regression results for various productivity measures for the outbound processes. The efficiency measure of productivity in this case is the ratio of sales by calls per day. The call centers gain profits of the workers receive high number of sales per day by making less number of calls to customers. The average number of sales made per days declines by 30% on high pollution days, which is a huge effect. The point estimate is 16.1 and the average sales made on low pollution days is 54.26 (see column 1 of Table 5). This effect is significant at the 10% level. When we add worker fixed effects, the effect declines to 27.4% but remain significant.

For the efficiency variable for outbound processes, there is a 14.6% decline in sales per day on high pollution days. The point estimate is 0.06 and the average sales per calls ratio on low pollution days is 0.41 (see column 3 of table 5). The point estimate and standard errors remain the same with worker fixed effect (column 4 of Table 5). This effect is significant at the 5% level. The last productivity measure for outbound processes is number of calls made, which is insignificant with large standard errors of 9.9 (column 5 and 6 of Table 5). The point estimate is -8.44, which indicates that there is a reduction in calls made on high pollution days. The average calls made on low pollution days is 134 approximately. The effect remains small and insignificant with worker fixed effects (column 6 of Table 5).

2.5.3 Robustness Checks

In this section, we address the concerns of serial correlation in productivity within a process and temperature controls confounding the results. The first concern is mitigated by clustering at the process-level instead of city-date level. Table 6 reports the results of productivity both at the extensive and intensive margins (standardized) with clustering at the process level (columns 1, 2, 3 and 5 in Table 6). Since there are few processes, we bootstrap the estimates and report the resultant p-values. The point estimates correspond with those in Tables 1 and 2. However, the combined productivity (z-score) is not significant only at the 5% level, instead of 10% level in Table 2.

The second concern is mitigated by removing temperature controls (columns 4 and 6 in Table 6). The point estimate for intensive margin of productivity is 0.14 SD without temperature controls, than the coefficient of 0.19 SD in Table 3 with temperature controls (column 4). This is still significant so temperature controls are not impacting the analysis much. Even on the extensive margin of productivity (column 6 of Table 6), we find insignificant impact of pollution on attendance without any temperature controls.

2.6 Conclusion and Way Forward

In this paper, we study the relationship between air pollution and productivity of individual workers in two call centers in India with centers across five cities. We find a precisely estimated null-effect of high $PM_{2.5}$ levels on the extensive margin of productivity (attendance). On the intensive margin of productivity, we find an overall 0.19 SD effect of high $PM_{2.5}$ levels compared to the average productivity below 35.4 $PM_{2.5}$ level.

As a part of the next steps of the paper, we are considering collecting productivity data from the call centers for at least one year, depending on feasibility.[6] A year-long data anaylsis will

[6] Due to COVID-19 related lock-down in India, the call centers are unable to retrieve the data from their

include all the fluctuations in the pollution level, related to seasonal variations across a year and will strengthen the anaylsis. It will increase the power to detect small effects, especially the results on productivity at the intensive margin for outbound processes.

In the future, we also plan to explore contacting the call center workers and collecting additional information through survey method, on their underlying health conditions. There is evidence in the health literature that particulate matter can exacerbate symptoms of asthma and other respiratory diseases (Williams et al., 2019). So, the impact of pollution on productivity for agents with respiratory and lung diseases is likely to be worse. We would also collect information on the area code of agents to account for traffic en-route to work. The individuals who travel from a greater distance are more exposed to air pollution and are likely to have worse productivity outcomes. Additionally, we will survey them on their mode of transport to work, to be able to study the exposure to pollution en-route to work.

servers and send it to us. So, for this study we have only used the data previously collected during the randomized controlled trial conducted by the dissertation author, Deepshikha.

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ACKNOWLEDGEMENTS

This paper is co-authored with my co-advisor Sarojini Hirshleifer. The dissertation author is the co-primary investigator and author of this paper.

We are grateful to the CEOs and center heads of partner call centers, Anil Sinha, Rajeev Jha and Sujit Sharma of Call-2-Connect and Kapil Sharma, Lakhan Joshi and Soham Ghosh of Five Splash for sharing their data and offering their support.

We appreciate the help of Mr. Anshuman Gaur, Private Secretary to Minister for Law and Justice & Electronics and IT and Mr. Rajiv Kumar, Joint Secretary at Ministry of Electronics and IT at Government of India (MEIT: GOI); Mr. Devesh Tyagi, Senior Director at Software Technology Parks of India (STPI), Mr. Madhurjya Prakash Baruah, Additional Director at STPI and Mr. K.P.S. Keshri, President of Bihar Industries Association (BIA) for introducing and recommending this project to call centers.

All views expressed in this paper are those of the authors alone and need not necessarily reflect those of the call centers, MEIT: GOI, STPI or BIA.

2.7 Tables

Table 2.1: Sample Statistics

	(1) Mean	(2) Standard Deviation	(3) Max	(4) Min	5 Observations
Pollution levels ($PM_{2.5}$)					
Mumbai	34.29	18.59	101.8	12.8	8,863
Noida	150.33	83.06	378.3	21.3	7,469
Patna	52.92	23.76	131.9	13.7	7,501
Udaipur	37.21	11.23	78.3	19.1	9,534
Hubli	25	26.5	120.1	3.7	7,386
Extensive margin of productivity					
Attendance	0.77	0.42	1	0	52,858
Intensive margin of productivity					
Inbound Process					
Average Call Handling Time (ACHT) in seconds	900.2	1057.24	3595	0	19,218
Logged-in Hours	7.9	2.5	16.93	0	19,218
Calls Received	122.26	85.76	530	0	19,218
Outbound Process					
Sales	64.92	72.95	497	0	21,518
Ratio of sales by calls per day	0.37	0.31	1	0	21,518
Calls made	179.78	93.02	604	0	21,518

Table 2.2: Impact of Air Pollution on Attendance

	Attendance	*Attendance*	*Attendance in Inbound Processes*	*Attendance in Inbound Processes*	*Attendance in Outbound Processes*	*Attendance in Outbound Processes*
High $PM_{2.5}$ levels	0.008	0.002	0.002	-0.003	0.027	0.015
	(0.01)	(0.009)	(0.013)	(0.011)	(0.022)	(0.021)
Temperature	0.004	0.014**	0.047***	0.07***	0.007	0.001
	(0.007)	(0.007)	(0.014)	(0.013)	(0.015)	(0.014)
Temperature squared/1,000	-0.011	-0.078*	-0.244***	-0.385***	-0.048	-0.008
	(0.043)	(0.042)	(0.078)	(0.071)	(0.102)	(0.097)
Observations	52,858	52,858	26,283	26,283	26,575	26,575
Mean of acceptable $PM_{2.5}$ levels	0.768	0.768	0.737	0.737	0.815	0.815
Worker FE	No	Yes	No	Yes	No	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Process FE	Yes	No	Yes	No	Yes	No

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes a sample of males and females in the call centers in Mumbai, Noida, Patna, Udaipur and Hubli for a period of 6 to 24 weeks depending on data availability. High air pollution is $PM_{2.5}$ above 35.4 which is deemed unhealthy by both WHO and EPA air quality standards. Attendance is an indicator variable for whether an employee was present or absent on any day from the first till the last day that they showed up in the data. Temperature measure is in degrees Fahrenheit. Standard errors are clustered at the city-date level.

Table 2.3: Impact of Air Pollution on Employee Productivity (Standardized)

	Productivity	*Productivity*	*Productivity in Inbound Processes*	*Productivity in Inbound Processes*	*Productivity in Outbound Processes*	*Productivity in Outbound Processes*
High $PM_{2.5}$ levels	-0.193***	-0.192***	-0.119**	-0.127***	-0.459**	-0.420**
	(0.066)	(0.063)	(0.050)	(0.044)	(0.197)	(0.199)
Temperature	0.080	0.075	0.109	0.091	-0.161	-0.123
	(0.072)	(0.070)	(0.073)	(0.059)	(0.134)	(0.132)
Temperature squared/1,000	-0.404	-0.342	-0.643	-0.497	1.382	1.126
	(0.407)	(0.398)	(0.401)	(0.330)	(0.842)	(0.830)
Observations	40,753	40,753	19,235	19,235	21,518	21,518
Mean of acceptable $PM_{2.5}$ levels	0	0	0	0	0	0
SD of acceptable $PM_{2.5}$ levels	0.99	0.99	0.99	0.99	0.99	0.99
Worker FE	No	Yes	No	Yes	No	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Process FE	Yes	No	Yes	No	Yes	No

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Standard errors are in parentheses. This includes a sample of males and females in the call centers in Mumbai, Noida, Patna, Udaipur and Hubli for a period of 6 to 24 weeks depending on data availability. High $PM_{2.5}$ levels is $PM_{2.5}$ above 35.4 which is deemed unhealthy by both WHO and EPA air quality standards. Productivity variables are standardized within a process using pollution level ($PM_{2.5}$) less than 35.5 level as control. Temperature measure is in degrees Fahrenheit. Standard errors are clustered at the city-date level.

Table 2.4: Impact of Air Pollution on Productivity in Inbound Processes

	Average call handling time (seconds)	*Average call handling time (seconds)*	*Login hours*	*Login hours*	*Calls answered*	*Calls answered*
High $PM_{2.5}$ levels	75.85	42.05	0.31**	0.24*	-7.42*	-7.81**
	(70.816)	(32.505)	(0.139)	(0.140)	(3.771)	(3.119)
Temperature	-148.599*	-38.233	-0.039	0.079	3.543	4.730
	(80.714)	(40.083)	(0.161)	(0.165)	(5.187)	(4.316)
Temperature squared/1,000	923.600**	218.012	-0.076	-0.719	-21.034	-26.101
	(440.096)	(223.787)	(0.881)	(0.911)	(29.082)	(24.403)
Observations	19,235	19,235	19,235	19,235	19,235	19,235
Mean of acceptable $PM_{2.5}$ levels	784.5	784.5	7.72	7.72	111.7	111.7
Worker FE	No	Yes	No	Yes	No	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Process FE	Yes	No	Yes	No	Yes	No

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes a sample of males and females in the call centers in Udaipur, Patna and Hubli for a period of 6 to 18 weeks depending on data availability. High $PM_{2.5}$ levels is $PM_{2.5}$ above 35.4 which is deemed unhealthy by both WHO and EPA air quality standards. Low average call handling time, high logged-in hours and high number of calls answered is profitable for the firm. Temperature measure is in degrees Fahrenheit. Standard errors are clustered at the city-date level.

Table 2.5: Impact of Air Pollution on Productivity in Outbound Processes

	Daily sales	*Daily sales*	*Sales by calls per day*	*Sales by calls per day*	*Calls made*	*Calls made*
High $PM_{2.5}$ levels	-16.1*	-14.9*	-0.06**	-0.06**	-8.44	-6.65
	(9.173)	(8.957)	(0.028)	(0.029)	(9.937)	(9.647)
Temperature	5.442	5.874	-0.014	-0.012	13.416*	14.546**
	(5.150)	(5.014)	(0.018)	(0.018)	(6.921)	(6.821)
Temperature squared/1,000	-46.723	-48.827	0.154	0.134	-99.942**	-106.063**
	(33.268)	(32.595)	(0.111)	(0.112)	(45.551)	(45.232)
Observations	21,518	21,518	21,518	21,518	21,518	21,518
Mean of acceptable $PM_{2.5}$ levels	54.26	54.26	0.412	0.412	133.9	133.9
Worker FE	No	Yes	No	Yes	No	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Process FE	Yes	No	Yes	No	Yes	No

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Standard errors are in parentheses. This includes a sample of males and females in the call centers in Mumbai, Noida, Patna and Hubli for a period of 6 to 24 weeks depending on data availability. High $PM_{2.5}$ levels is $PM_{2.5}$ above 35.4 which is deemed unhealthy by both WHO and EPA air quality standards. High number of sales, high sales call ratio and less calls made is profitable for the firm. Temperature measure is in degrees Fahrenheit. Standard errors are clustered at the city-date level.

Table 2.6: Robustness Checks

	Productivity	*Productivity in Inbound Processes*	*Productivity in Outbound Processes*	*Productivity*	*Attendance*	*Attendance*
High $PM_{2.5}$ levels	-0.192**	-0.127	-0.420***	-0.141**	0.002	0.004
	(0.060)	(0.062)	(0.041)	(0.061)	(0.012)	(0.008)
Temperature	0.075	0.091	-0.123		0.014	
	(0.076)	(0.068)	(0.173)		(0.010)	
Temperature squared/1,000	-0.342	-0.497	1.126		-0.078	
	(0.451)	(0.414)	(1.135)		(0.058)	
Observations	40,753	19,235	21,518	40,753	52,858	52,858
Mean of acceptable $PM_{2.5}$ levels	0	0	0	0	0.76	0.76
Clustering	Process level	Process level	Process level	City-date	Process level	City-date
p-value(bootstrap)	0.004	00	0.12	0.09	0.9	0.7
Temperature control	Yes	Yes	Yes	No	Yes	No
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Process FE	No	No	No	No	No	No

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are in parentheses. This includes a sample of males and females in the call centers in Mumbai, Noida, Patna, Udaipur and Hubli for a period of 6 to 24 weeks depending on data availability. High $PM_{2.5}$ levels is $PM_{2.5}$ above 35.4 which is deemed unhealthy by both WHO and EPA air quality standards. Productivity variables are standardized within a process using pollution level ($PM_{2.5}$) less than 35.4 level as control. Attendance is an indicator variable for whether an employee was present or absent on any day from the first till the last day that they showed up in the data. Temperature measure is in degrees Fahrenheit.

Chapter 3

Effect of Co-residence with Parents-in-law on Female Labor Force Participation

Abstract

This paper studies the impact of co-residence with mother-in-law and father-in-law on women's labor force participation. We study this in the Indian context where co-residence with parents-in-law is a common practice and women don't have much decision-making autonomy or empowerment in the presence of a parent-in-law in the household. On the other hand, for women with young children, having a mother-in-law or father-in-law living nearby might have a positive effect on labor supply because the grandparents might provide childcare transfers. We use two rounds of IHDS panel data for the analysis taking death of the parent-in-law as the exogenous variation. Our preliminary results show that co-residence with father-in-law has a significantly negative effect on women's labor supply. Losing one's healthy father-in-law increases the labor force participation of women by overall 11.4 percentage points, compared to a similar household where the father-in-law still co-resides in the second round. This is a large increase in female labor force participation (FLFP) of approximately 25% over the mean FLFP in the first round. There is also an increase in FLFP by 11 percentage points following the loss of a working mother-in-law, providing evidence of an added worker effect in the household. Death of mother-in-law increases women's empowerment by 16.7%.

3.1 Introduction

Despite very rapid economic growth in India in the recent years, there has been a steady decline in Female Labor Force Participation (FLFP) rates across all age groups and education levels in India (Bourmpoula et al., 2014)). In fact the FLFP rates in India have declined by more than 8 percentage percentage points between 1999 and 2009 among married women (Afridi et al, 2016).[1] There is some evidence that women in India may be withdrawing from the workforce to cater to their traditional role at home as care workers.[2] This is an expected outcome owing to the increases in number of elderly and the rise in the number of joint families in India over this period.[3] Therefore, it has become important to study the labor market outcomes of women living in the traditional set up of joint families to explain some of the decline in FLFP in the last two decades. Additionally, with the expected increase in elder-care requirements within the households in the future, this study has important policy implications.

This paper studies the impact of co-residing with mother-in-law and father-in-law on woman's labor force participation as the primary outcome in the Indian context. We use two waves of the panel data set, India Human Development Survey (IHDS), and take the sample of women in the first round who co-reside with healthy parents-in-law. Death of healthy parent-in-law is used for identification in the second round. We find that losing one's father-in-law increases the labor force participation of women by 5 to 13 percentage points, compared to a similar household where the father-in-law still co-resides in the second round. This is a large increase in female labor force participation (FLFP) of approximately 11% to 25% over the mean FLFP in the first round. There

[1] The education levels have risen and fertility has decreased simultaneously during this period, adding to the puzzling decline in FLFP.

[2] According to NSSO data, about 88% of the rural women in 2004-05 required to spend most of their time on domestic duties, which increased to 92% in 2011-12. About 55% rural women reported to be engaged in domestic work as no other person was available to do that work and this increased to 62% in 2009-10.

[3] Joint families are those where more than one married couple co-resides, and patriarchal nature of Indian society leads to a high prevalence of inter-generational co-residence. Joint families in India constitute about 27-30% of all families and between the time period 2000 to 2010, number of joint families as a percentage of all families increased marginally. Between 2000 and 2010 the percentage of nuclear families as a percentage of all families declined slightly, from 70.34% to 70.11% and number of joint families increased (Census Reports).

is also an increase in FLFP by 11 percentage points following the loss of a working mother-in-law, providing evidence of an added worker effect in the household. We also study empowerment as a secondary measure and find that death of the mother-in-law increases women's empowerment by 16.7%.

Patrilocality or living with parents-in-law after marriage is a common phenomenon for women in India. Women often don't have much decision-making autonomy, especially in the presence of a parent-in-law in the household. There are some descriptive studies showing that living with a mother-in-law is associated with diminished autonomy for a woman in India owing to the fact that mother-in-law is the head's wife (Bloom, Wypij and Das Gupta, 2001; Jejeebhoy and Sathar 2001; Balk 1994). Mason (1997) also discuss how the household head's wife has more decision-making power than the "junior" wives in joint families in India. This study is relevant for other countries as well, because many other countries practice the family structure of inter-generational co-residence or co-residence of adult sons and elderly parents especially in Asia, the Middle East, and North Africa and Latin America (Ebenstein, 2014).

The primary outcome variable is labor supply of women. Due to under-valuation and lack of recognition of women's unpaid work, the gender bias in a patriarchal society is exacerbated if women do not contribute to the household income, making earned income an important indicator of women's well being and autonomy. In these societies, where sons are preferred and women's position is low, less household resources are spent on the education and health of a girl than a boy (Jayachandran, 2015). Rob Jensen (2012) provides evidence for this in his paper where there was an increase in FLFP in a northern state of India due to the increase in white-collar jobs available for women in that region. He shows that this increase in FLFP affected the human capital and fertility decisions of girls/women and was associated with increased enrollment of school-aged girls and improvements in their body mass index (BMI). Singh and Samara (1996) use Demographic Health Survey (DHS) data for 40 countries to show how age at marriage of a woman positively correlates with urbanization, women's education and FLFP. Therefore, women's earned income is crucial for better health, nutrition and human capital investments on girl children and for a decrease in early marriage and child bearing for women. Another reason how wage work benefits women is because it raises their bargaining power at home. Anderson and Eswaran (2009) have empirically shown using cross-sectional data set from Matlab Health and Socio-economic Survey (1996) from Bangladesh, that it is earned rather than unearned income that boosts women's relative bargaining power and autonomy. Majlesi (JDE, 2016) uses trade shocks as exogenous demand shifts in different manufacturing industries to show how women's relative bargaining power at home increases in an instance of favorable shocks to manufacturing industries with more women workers in Mexico.

Economic theory makes no clear prediction about the effect of living close to one's father-in-law or mother-in-law on labor supply (at the extensive margin- the probability of working in the market, or at the intensive margin- the number of hours worked per week). Konrad et al. (2002) model migration away from parents as a non-cooperative game in which the eldest child always has the first mover advantage and migrates away from home to avoid future transfers of care to elderly parents. Rainer and Siedler (2009) work on a similar model and show that only children are more likely to be living in parents' location and therefore have worse labor market outcomes than children with siblings. None of these papers consider the positive effect of the receipt of childcare on the labor force outcomes of women with children.

Masaru Sasaki (JHR, 2002) try to study the impact of this in the Japanese context and also find that co-residence with parents or in-laws has a significantly positive impact. However, they use cross-sectional data of Japanese household survey which raises significant concern about omitted variable bias. Further, it can be that co-residence and female labor force participation (LFP) decisions are taken together such that there is endogeneity issue. Arpino, Pronzato and Tavares (2011) estimate the effect of grandparent-provided childcare on the labor force participation of women in Italy using a cross-sectional data set and doing the analysis on young mothers with at least one child below 14 years of age. They use the number of living grandparents as an instrument for grandparent help in childcare. They find a huge (30 percentage point) positive effect of grandparent care transfers on the probability that a woman is working but because the instrument doesn't meet the exclusion restriction (due to correlation with unobservable characteristics of the family like genetic endowment) the coefficient again may be subject to biased.

Another study that looks at this issue using richer data is by Compton and Pollak (2014). They use the National Survey of Families and Households (NSFH) and the public use files of the U.S. Census to study the effect of proximity to mother or mother-in-law on a married women's labor force participation. They see the impact on women who have young children less 12 years of age and find that the probability of living within 25 miles of their mothers or mothers-in-law increases the probability of working in the market and also increases the number of hours worked per week.

Apart from these evidences from the developed world, there a study by Anukriti et al. (2020) that studies the impact of co-residence with parents-in-law on outcomes such as women's mobility and their reproductive health in one of the states in India. However, there is no empirical study which studies nature of co-residence in joint family systems and woman's labor force participation as the primary outcome. In such a family structure parents-in-law have a more crucial role in a woman's decision to do wage work. Using household time allocation, Becker's model (1965) of female labor supply makes assumptions that women make their labor supply decisions not only considering their leisure and labor trade-offs, but they also take into consideration home production of goods and services, and care work. As it is true that all over the world women face the disproportionate burden of care work, which includes the 3 C's of cooking, cleaning and care work (OECD Time-use Data), studying women's labor supply, taking into consideration women's time constraints is essential. And often times, women get help in these activities from other females co-residing with them or living nearby. Due to lack of reliable formal childcare, presence of mother-in-law can partially release the daughter-in-law of this responsibility. Hence, distribution of domestic work within a household among women plays a role in ascertaining the labor supply of women in a household. Since, the younger woman or daughter-in-law is likely to have a higher marginal productivity of market work than the older woman, but similar marginal productivity of home-based work, households may prefer the daughter-in-law to do wage work. There could also be a generational divergence of preference with mother-in-law preferring unpaid work and daughter-in-law preferring paid work.

Alternatively, co-residence with parents-in-law might have a negative effect on labor supply because the grandparents themselves may require care, and caregiving responsibilities often fall to daughters-in-law who co-reside with them. To tackle this problem only healthy parents-in-law are included in the analysis, i.e., parents-in-law with no major morbidities like Tuberculosis, Cancer, AIDS etc. in the first round are included.

In developing countries like India where genders are socially segregated, there are risks and costs associated with physical mobility of women, resulting in household preference of women to stay at home. These perceived costs arise from concerns of safety in an environment of rampant sexual harassment and sexual violence. It can also stem from protecting the family honor from risks of intermingling of women with 'outside men' (Jayachandran, 2015). Therefore, for a woman to participate in the labor market, wage should compensate for both shadow value of home-based work and cultural costs. These costs are higher in a joint family structure and could depress the woman's labor supply.

As there are many opposing mechanisms through which the labor supply of women is affected in a joint family structure, to learn which of these effects predominate requires empirical analysis. Since there could be potential endogeneity between co-residence with parent-in-law and woman's LFP as women who live with their mother-in-law could be very different from those that don't live with them. Also, there could be simultaneity issue. To take care of the unobserved differences, death of mother-in-law and father-in-law are used as the exogenous variation.

These effects on daughter-in-law's labor supply could be different depending on whether the loss is of a mother-in-law or father-in-law. If there is a death of a wage earning parent-in-law, then the woman might join the labor market to compensate for the loss of income to the household (added worker effect). However, death of a mother-in-law can also posit as a home production shock.

3.2 Data and Descriptive Statistics

For this study, we use two waves of the panel data set, India Human Development Survey (IHDS). IHDS is a nationally representative survey of more than 40,000 households. The first round is for the year 2004-2005 and the second round is for the year 2011-12. The survey covers topics concerning health, education, employment, economic status, marriage, fertility, gender relations, and social capital. Information on whether the mother-in-law is co-residing with the woman in the first round is obtained from the household roster. The sample is limited to daughters-in-law who are in the age group 18 to 49 in the first round. As death of parent-in-law is used for identification, women who co-reside with their parent-in-law in the first round are chosen for the analysis. Labor force outcomes of those who lose their parents-in-law are then compared to those who are still co-residing with them.

As parents-in-law could be co-residing with their son and daughter-in-law for care transfers if they suffer from any major morbidities or long-term illnesses, it would require that the daughter-in-law stay at home for the same. However, we want to separate out this effect and make death of a parent-in-law an exogenous shock to the household. So, we only take parents-in-law who are 'healthy' in the first round for the analysis. 'Healthy' here is defined as those suffering from no major morbidities like Cancer, Asthma Tuberculosis, Heart Diseases, Polio, Leprosy, Paralysis, Diabetes, STD/AIDS, Epilepsy any form of Mental Illness, high blood pressure problems or any other long term disease. Even if they suffer from one of these diseases, they are not included in the analysis.

Therefore, families with both healthy mother-in-law and father-in-law are chosen because if even one has a long-term disease, the labor supply of daughter-in-law will be affected by it.

Table 1 reports the summary statistics to see if the two groups (the one in which woman co-resides with her parent-in-law and one in which one of them dies by the second rounds) in 2005 are similar on variables like Household Assets, Woman's education level, Family size and Number of children. It can be seen that the women who lose their parents-in-law are older and therefore are less educated on an average (measured in number of years of education). As these families are generally older, there are fewer children in the house. The labor force participation is lesser in comparison to the group that does not co-reside with their mother-in-law. Table 7 in the Appendix reports the characteristics of mothers-in-law in 2005 belonging to the two groups. Here we have included both healthy and unhealthy mothers-in-law. About 40% of the mothers-in-law worked for more than 240 hours in 2005. Table 8 in the Appendix reports the average characteristics of all fathers-in-law co-residing with daughters-in-law in 2005 divided by the two groups of concern. I use the entire set of fathers-in-law co-residing with their daughter-in-law (both healthy and unhealthy) and as expected find that the ones with more diseases are likely to die.

For the first specification, the sample is restricted to those women who live/co-reside with their mothers-in-law in the first period, which is around 9159 women out of 45,895 sample women. In the second round, co-residence is again computed through the household roster and crosschecked using the tracking file. Hence, we are able to differentiate between women who are still co-residing with their mothers-in-law, women who lost their mothers-in-law between the two rounds and women who don't co-reside with their mothers-in-law any more. Out of 9159 daughters-in-law co-residing with their mothers-in-law in the first round, 1,948 (about 21%) of them lose their mothers-in-law and the rest continue to live with them in the second round. Split households are excluded from the sample. Among these, only 7,200 of the women live with healthy mother-in-law (and healthy father-in-law if father-in-law also co-resides with them) in the first round of which 1,493 die by the second round of short term illnesses and accidents and 5,707 of them are still co-residing with them.

For the second specification, the sample is restricted to women who co-reside with their fathers-in-law in the first round. This is around 6,777 daughters-in-law, out of whom about 2,293 of them lose their father-in-law by the second round. In the sub-sample of 5,226 women co-residing with healthy father-in-law, 1,670 of them lose their fathers-in-law and 3,556 is the comparison group of those still co-residing with their fathers-in-law in the second round.

In the third specification, women co-residing with both healthy parents-in-law in 2005 are chosen, which is a total of 3,850, out of which 429 lose their mother-in-law, 870 lose their father-in-law and 208 lose both their parents-in-law to short-term illnesses and accidents by the second round. A total of 11,633 women live with either their of parents-in-law (who is of good health) in 2005 in the sample out of which 2,979 (about 25%) of them lose either or both of them by 2011.

To understand how co-residence with parents-in-law impacts empowerment of women in India, we construct measures of Physical Autonomy, Financial Autonomy and Decision-making Autonomy for women in both rounds. The measure of Physical Autonomy is based on questions on whether they require permission to visit the health centre, visit friends/ relatives or for going for grocery shopping. The measure of Financial Autonomy is based on questions on whether they have cash in hand to spend on household expenditures. have bank account or have home ownership or rental papers in their names. And the measure of Decision Autonomy is based on who in the household makes the decision on what to cook, what to do if child falls sick, buy expensive items like fridge/TV, how many children the woman has and about child's marriage. Average responses on whether daughter-in-law has the most say on these measures is calculated. A combined measure of empowerment is estimated taking an average of Physical Autonomy, Financial Autonomy and Decision-making Autonomy responses.

3.3 Empirical Methodology

We use the following empirical specifications to estimate the effect of co-residence with mother-in-law and father-in-law on various outcome measures of labor force participation, autonomy and empowerment. Using a panel data of women, we control for individual and time fixed effects to take into account time invariant individual heterogeneity and time trends. The main outcome variable labor force participation (LFP) is a binary variable, which takes value one if woman reports working for more than 240 hours in a year on any work (farm or off-farm work, wage or self-employed work). To allow for flexibility in age, we use the full set of age dummies. Standard errors are clustered at the primary sampling unit to account for unobserved but correlated characteristics affecting outcomes among women from the same primary sampling unit or district in the data -set.

In the first methodology, as discussed in the previous section, women co-residing with healthy mother-in-law are chosen and the effect of death of mother-in-law on labor supply of daughter-in-law is discussed with those still co-residing with the mother-in-law. This sub-sample also contains healthy father-in-law for some families, who are co-residing with both their parents-in-law in 2005.

$$\mathrm{LFP}_{it} = \beta_0 + \beta_1 \mathrm{Death\,of\,Motherinlaw}_{it} + \beta_2 \mathrm{Age}_{it} + \Omega_i + \epsilon_{it} \tag{3.1}$$

In the second specification, women co-residing with healthy father-in-law are chosen and the effect of death of father-in-law on labor supply of daughter-in-law is discussed with those still co-residing with the father-in-law. This sub-sample also contains healthy mother-in-law for some families.

$$\mathrm{LFP}_{it} = \beta_0 + \beta_1 \mathrm{Death\,of\,Fatherinlaw}_{it} + \beta_2 \mathrm{Age}_{it} + \Omega_i + \epsilon_{it} \tag{3.2}$$

In the following specification, families co-residing with both parents-in-law are chosen and to capture the differential effects of each of the following, death of mother-in-law, death of father-in-law and death of both are used in the regression analysis and the group of women which is still co-residing with both the parents-in-law in the second round is used as comparison. Here $\mathrm{Y_{it}}$ are the primary outcomes measures of labor force participation and secondary outcome measures of autonomy and empowerment of women.

$$
\begin{aligned}
\mathrm{Y}_{it} &= \beta_0 + \beta_1 \text{Death of Motherinlaw}_{it} + \beta_2 \text{Death of Fatherinlaw}_{it} \\
&+ \beta_3 \text{Death of Motherinlaw and Fatherinlaw}_{it} + \beta_4 \text{Age}_{it} + \Omega_i + \epsilon_{it}
\end{aligned}
\tag{3.3}
$$

The regression results of these three empirical methodologies are discussed in the following section. We also conduct some heterogeneity analysis. So, sub-group analysis is done for Urban and Rural areas as the FLFP varies in the two greatly in India. In addition, we analyze the labor force participation of women with children separately to check if the woman withdraws from the labor market to provide child care transfers in the absence of parents-in-law. Families which lose an employed parent-in-law are also discussed separately to see if there is evidence of any added worker effect owing to the negative income shock to the household.

3.4 Regression Results

This section provides an overview of the main results. The first subsection provides the regression results on both the primary outcome of female labor force participation and the secondary outcome of female empowerment. We also provide results for some heterogeneous groups where the result are expected to be theoretically different. In the second subsection, the results from some robustness checks are discussed.

3.4.1 Main Results on Primary and Secondary Outcomes

In Table 2, we provide regression results on the effect of death of healthy mother-in-law on the primary outcomes of labor force participation of daughter-in-law. There is no evidence of co-residence with mother-in-law for the full sample as well as for the sub-sample of women with children and women living in both rural and urban areas (Columns 1, 2, 3 and 4 in Table 2). Table 2 also shows that the average labor force participation rates of women co-residing with mothers-in-law is much lesser in urban areas at 19.3% in the sample than those in rural areas at 58%. The LFP of women with children below the age of 14 in he household for those co-residing with parents-in-law is about 51% in 2005. The women with children are also the younger women in the sample.

We find a 11.1 percentage point increase in women's LFP rates following the death of a healthy and working mother-in-law (Column 5, Table 2). This is a 19% increase over the mean FLFP of 0.57 in 2005 and is significant at the 5% level. We don't find any effects for the death of a non-wage earning mother-in-law on FLFP. Therefore, it appears that women are working to compensate for the negative income shock to the household.

A similar analysis on fathers-in-law shows a positive, strong and robust result on FLFP. We also observe that the women who co-reside with healthy fathers-in-law have a lower mean LFP in 2005 than those who live with healthy mothers-in-law (Table 2 and 3). We find an overall 11.4 percentage point increase in FLFP because of the death of father-in-law over the mean FLFP of 0.48 in the first round. This is significant at the 1% level and is a increase of approximately 24% (See Column 1 of Table 3).

For rural women, the point-estimate increase to 12.2 which is a 22.5% increase in FLFP following the death of a healthy father-in-law (Column 2 of Table 3. For urban women, the effect is smaller at 8 percentage points but this is significant at the 5% level (Column 3 of Table 3. This is a 56% increase in FLFP in urban areas for the women in the sample. We find similar effects of 12.1

percentage points on FLFP in households with children, which is a 25% increase (Column 4 of Table 3). Women with children are younger so they might find it easier to go back to the labor market.

Although the FLFP rates in 2005 were almost the same for women co-residing with working and non-wage working father-in-law, we find a stronger effect of 13.2 for working father-in-law compared to the 5.5 percentage point effect for non-wage working father-in-law (Columns 5 and 6 of Table 3). As expected, women enter the labor market to compensate for the income shock to the household after a working father-in-law's death. This is a 25% increase significant at the 1% level. Surprisingly, we also find an increase in FLFP after the father-in-law's death even if the father-in-law was not working. This effect is significant at the 10% level and is a 11% increase in FLFP.

In Table 4, we provide regression results for the sub-sample which co-resides with healthy parents-in-law in the first round. We study this separately because it helps us in understanding the overall impact of death on one of the parents-in-law compared to the death of both parents-in-law on FLFP. Overall, we find that while co-residing with both parents-in-law, the death of just the father-in-law increases FLFP by 12.2 percentage points, which is significant at the 1% level (Column 1 of Table 4). We find similar effects for both rural and urban women (Columns 2 and 3 of Table 4). For households with younger children and therefore also younger daughters-in-law, death of just the mother-in-law also increases the FLFP significantly by 14.5 percentage points over the mean FLFP of 0.505 in 2005 (Column 4 of Table 4). For this case death of just the father-in-law also increases FLFP by 13.7 percentage points. But the death of both parents-in-law reduces the overall FLFP by 18.8 percentage points (Column 4 of Table 4). This is significant at the 10% level. This result indicates that the parents-in-law are providing some care transfers because in the absence of both parents-in-law, women with children have to withdraw from the labor market.

The regression results on the secondary outcome measures of autonomy or empowerment provide evidence that daughter-in-law's empowerment increases following the death of a healthy mother-in-law. It is a 4.7 percentage point increase over a mean of 0.28, which is a 16.7% increase

(Column 4 of Table 5). This is significant at the 1% level. There is no impact of father-in-law's death on measures of physical, financial and decision autonomy (Table 5). We also observe that only 20% of the women in the sample have most say on their physical autonomy or decisions on visits to their friends and relatives.

3.4.2 Robustness Checks

There is a concern that the women who lose their parents-in-law are older and less educated on an average and therefore can't be compared (Table 1). Therefore, for a robustness check, women are matched on age, education, family size, household assets and location in urban/rural areas in the first round 2005. The summary statistics of the matched women are provided in Table 9 of the Appendix. As we can see, women are balanced on all the afore-mentioned characteristics. The common support graph in the appendix further illustrates that we have enough support and comparison for each age and education group.

In Table 6, we report similar but stronger results as Table 4. These effects are huge while comparing matched groups, indicating more than a 50% increase in FLFP following a healthy father-in-law's death. This further supports our analysis and confirms our results.

3.5 Conclusion

The effect of death of a healthy father-in-law on FLFP is an overall increase of 11.4 percentage points. This a large effect of around 24% increase in FLFP. This is also true for death of a working mother-in-law as it increases in FLFP by around 11 percentage points (a 19% increase). This provides evidence of the added worker effect due to a negative income shock to the household. The death of father-in-law in the household with the presence of mother-in-law, frees the woman to work in the labor force especially in the case of unanticipated income shocks. Labor supply of younger women with children responds more significantly and positively to the death of one of parents-in-law.

However, her labor supply declines if she loses both her parents-in-law, indicating that the death of both parents-in-law in leads to women withdrawing from the labor market. Therefore, there is some substitution of women's labor towards more unpaid home-based work from paid work in the absence of healthy parents-in-law (about 18.8 percentage point negative effect on FLFP).

It seems that women in India are secondary workers and their labor supply more of an insurance to the household against income shocks. The analysis has implications for policy as it suggests that policies that increase the availability of childcare to meet irregular or unanticipated child care needs, including care for a sick child, might substantially increase the labor supply of married women with young children. With increasing life expectancy and associated rise in old people in India and other countries. This analysis also makes contribution to the literature on ageing population, as it discusses the financial and care transfers of parents-in-law in the household. We would like to probe more into this in the future using data on health and well-being of children in the presence of grandparents.

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ACKNOWLEDGEMENTS

This paper is co-authored with my co-advisor Anil Deolalikar. The dissertation author is the co-primary investigator and author of this paper.

We are grateful to Mindy Marks, Joseph Cummins, Robert Kaestner, Steven Helfand and Michael Bates for their valuable comments at various stages of this paper. We also would like to thank the faculty and students at the Department of Economics at UC Riverside on their comments during various seminars in which this paper was presented. We also want to thank the audiences at IAFFE and APPAM seminars for their useful comments.

3.6 Figures

Figure 3.1: Female Labor Force Participation by Age in 2005

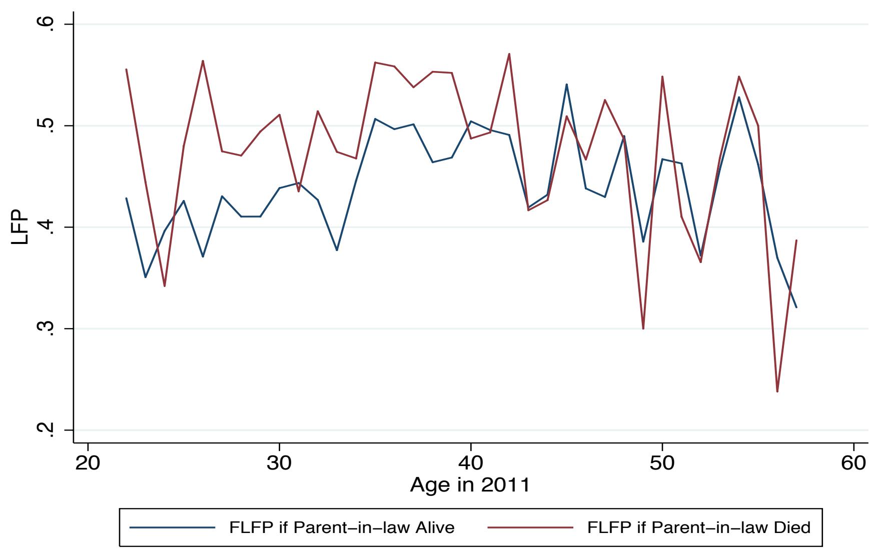

Figure 3.2: Female Labor Force Participation by Age in 2011

3.7 Table

Table 3.1: Summary Statistics of Women

	Total Sample	*Death of Parent-in-law*	*Alive and Co-residing Parents-in-law*
Woman's Age	28.70	32.45	27.45
	(8.491)	(9.308)	(7.811)
Woman's Education	4.48	3.92	4.67
	(4.650)	(4.526)	(4.676)
Family Size	8.03	7.43	8.23
	(3.527)	(3.055)	(3.649)
Number of Children	2.66	2.37	2.75
	(2.097)	(1.919)	(2.145)
Household Assets	14.03	13.89	14.08
	(5.913)	(5.870)	(5.927)
Number of Observations	11633	2979	8654

Notes: Average values are reported on the characteristics of women in our sample in 2005. These women co-reside with healthy parents-in-law in 2005. Standard deviations are in parentheses.

Table 3.2: Effect of Co-residence with Mother-in-law on Woman's Labor Force Participation

	Full Sample	*Rural Women*	*Urban Women*	*Households with Children*	*Working Mother-in-law*	*Non-wage Worker Mother-in-law*
Mother-in-law dead	0.022	0.026	-0.001	0.025	0.111**	-0.035
	(0.022)	(0.027)	(0.035)	(0.024)	(0.044)	(0.022)
Survey Year	-0.102***	-0.133***	0.025	-0.109***	-0.191***	-0.048*
	(0.025)	(0.028)	(0.036)	(0.027)	(0.044)	(0.025)
Constant	0.035	0.137	-0.211	0.045	0.146	0.344***
	(0.186)	(0.159)	(0.273)	(0.178)	(0.162)	(0.048)
Observations	14,400	10,890	3,510	12,164	6,934	11,310
R-squared	0.045	0.058	0.067	0.044	0.080	0.055
Number of Individuals	7,200	5,445	1,755	6,082	3,467	5,655
Mean LFP in 2005	0.508	0.586	0.193	0.514	0.571	0.466

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ 2005 and 2011 panel rounds of IHDS data are used with individual fixed effects and time fixed effect. Sample includes married women from the age 18 to 58 years, who are co-residing with healthy mother-in-law in 2005. We Control for age flexibly. Standard errors are clustered at the primary sampling unit (PSU).

Table 3.3: Effect of Co-residence with Father-in-law on Woman's Labor Force Participation

	Full Sample	*Rural Women*	*Urban Women*	*Households with Children*	*Working Father-in-law*	*Non-wage Worker Father-in-law*
Father-in-law dead	0.114***	0.122***	0.082**	0.121***	0.132***	0.055*
	(0.024)	(0.028)	(0.034)	(0.025)	(0.030)	(0.029)
Survey Year	-0.132***	-0.156***	-0.029	-0.137***	-0.126***	-0.079**
	(0.031)	(0.036)	(0.045)	(0.035)	(0.038)	(0.039)
Constant	0.339***	0.388***	-0.161	0.331***	0.336***	0.308***
	(0.050)	(0.055)	(0.226)	(0.055)	(0.052)	(0.072)
Observations	10,452	8,204	2,248	9,006	8,566	4,928
R-squared	0.053	0.066	0.094	0.058	0.062	0.071
Number of Individuals	5,226	4,102	1,124	4,503	4,283	2,464
Mean LFP in 2005	0.476	0.543	0.147	0.481	0.464	0.499

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ 2005 and 2011 panel rounds of IHDS data are used with individual fixed effects and time fixed effect. Sample includes married women from the age 18 to 58 years, who are co-residing with healthy father-in-law in 2005. We control for age flexibly. Standard errors are clustered at the primary sampling unit (PSU).

Table 3.4: Effect of Co-residence with Parents-in-law on Women's Labor Force Participation

	Full Sample	*Rural Women*	*Urban Women*	*Households with Children*
Mother-in-law dead	0.095	0.106	0.069	0.145**
	(0.063)	(0.073)	(0.068)	(0.072)
Father-in-law dead	0.122***	0.116***	0.141***	0.137***
	(0.031)	(0.037)	(0.045)	(0.033)
Both Parents-in-law dead	-0.127	-0.131	-0.169	-0.188*
	(0.088)	(0.102)	(0.117)	(0.100)
Survey Year	-0.126***	-0.154***	-0.006	-0.138***
	(0.037)	(0.042)	(0.043)	(0.040)
Constant	0.304***	0.339***	-0.253	0.295***
	(0.048)	(0.054)	(0.296)	(0.052)
Observations	7,680	5,988	1,692	6,572
R-squared	0.041	0.053	0.102	0.047
Number of Individuals	3,840	2,994	846	3,286
Mean LFP in 2005	0.498	0.567	0.183	0.505

Notes: *** p<0.01, ** p<0.05, * p<0.1 2005 and 2011 panel rounds of IHDS data are used with individual fixed effects and time fixed effect. Sample includes married women from the age 18 to 58 years, who are co-residing with both healthy mother-in-law and father-in-law in 2005. We control for age flexibly. Standard errors are clustered at the primary sampling unit (PSU).

Table 3.5: Effect of Co-residence with Parents-in-law on Women's Empowerment

	Physical Autonomy	*Financial Autonomy*	*Decision Autonomy*	*Total Empowerment*
Father-in-law dead	-0.012	0.026	0.022	0.011
	(0.028)	(0.022)	(0.025)	(0.016)
Mother-in-law dead	0.047	0.028	0.066	0.047*
	(0.033)	(0.033)	(0.048)	(0.026)
Both Parents-in-law dead	-0.134	-0.042	0.015	-0.053
	(0.083)	(0.053)	(0.072)	(0.047)
Survey Year	-0.169***	0.124***	-0.011	-0.018
	(0.032)	(0.026)	(0.028)	(0.019)
Constant	0.284***	0.180***	0.205***	0.222***
	(0.044)	(0.045)	(0.067)	(0.035)
Observations	4,502	4,502	4,502	4,502
R-squared	0.093	0.245	0.048	0.061
Number of Individuals	2,251	2,251	2,251	2,251
Mean Autonomy in 2005	0.198	0.429	0.212	0.280

Notes: *** p<0.01, ** p<0.05, * p<0.1 2005 and 2011 panel rounds of IHDS data are used with individual fixed effects and time fixed effect. Sample includes married women from the age 18 to 58 years, who are co-residing with both healthy mother-in-law and father-in-law in 2005. We control for age flexibly. Standard errors are clustered at the primary sampling unit (PSU).

Table 3.6: Robustness Check: Propensity Score Matching

	Full Sample	*Rural Women*	*Urban Women*	*Households with Children*
Mother-in-law dead	0.186	0.207	0.123	0.297**
	(0.138)	(0.158)	(0.137)	(0.147)
Father-in-law dead	0.266***	0.255***	0.271**	0.300***
	(0.070)	(0.075)	(0.111)	(0.078)
Both Parent-in-law dead	-0.333*	-0.385*	-0.343	-0.366*
	(0.186)	(0.214)	(0.294)	(0.195)
Survey Year	-0.333***	-0.370***	0.188	-0.277**
	(0.103)	(0.107)	(0.194)	(0.114)
Constant	0.494***	0.539***	0.099	0.540***
	(0.092)	(0.097)	(0.412)	(0.076)
Observations	1,088	872	216	981
R-squared	0.214	0.271	0.350	0.239
Number of IND_ID	544	436	108	534
Mean LFP in 2005	0.523	0.585	0.183	0.525

Notes: *** p<0.01, ** p<0.05, * p<0.1 2005 and 2011 panel rounds of IHDS data are used with individual fixed effects and time fixed effect. Sample includes married women from the age 18 to 58 years, who are co-residing with both healthy mother-in-law and father-in-law in 2005. Women are matched on age, education, family size, household assets and location in urban/rural areas in 2005. We control for age flexibly. Standard errors are clustered at the primary sampling unit (PSU).

3.8 Appendix

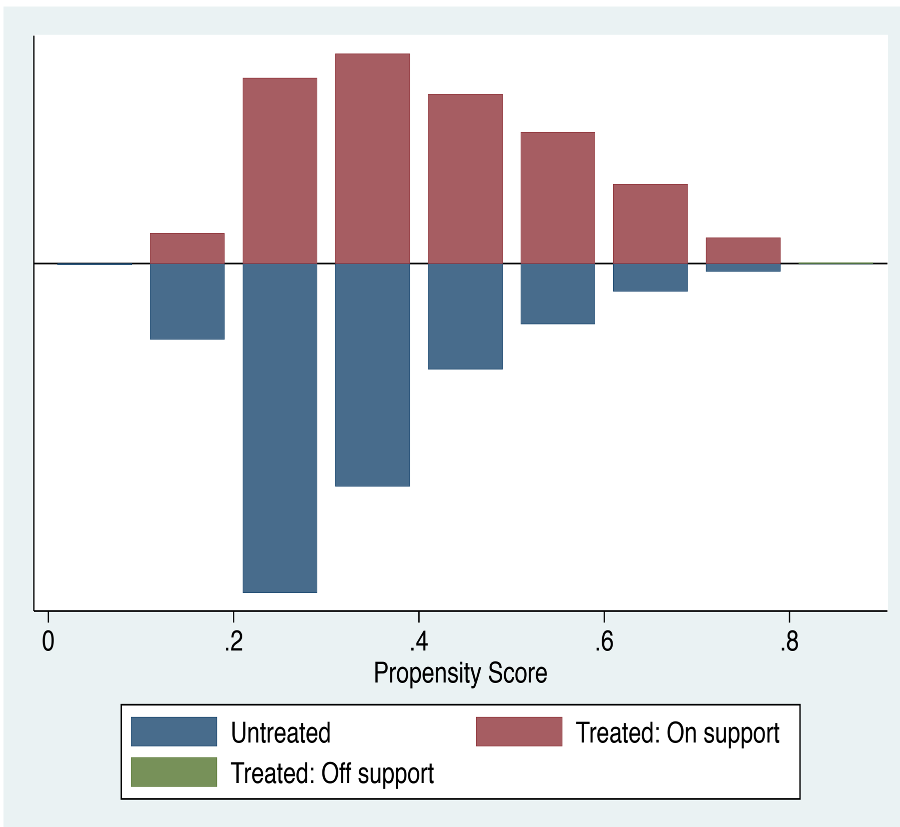

Figure 3.3: Propensity Score Matching: Common Support Graph

Table 3.7: Summary Statistics of Mothers-in-law in 2005

	Total Sample	*Dead Mother-in-law*	*Alive and co-residing Mother-in-law*
Education in years	1.28	0.68	1.47
	(2.759)	(2.160)	(2.891)
LFP	0.40	0.19	0.46
	(0.491)	(0.389)	(0.499)
Any Major Morbidities	0.15	0.21	0.13
	(0.358)	(0.411)	(0.340)
Number of Observations	9159	1948	7211

Notes: Average values are reported on the characteristics of mothers-in-law in our sample in 2005. This includes healthy and unhealthy mothers-in-law. Standard deviations are in parentheses.

Table 3.8: Summary Statistics of Fathers-in-law in 2005

	Total Sample	*Dead Father-in-law*	*Alive and Co-residing Father-in-law*
Education in years	3.74	2.58	4.38
	(4.532)	(4.079)	(4.640)
LFP	0.65	0.44	0.76
	(0.477)	(0.496)	(0.428)
Any Major Morbidities	0.16	0.22	0.12
	(0.363)	(0.417)	(0.328)
Number of Observations	6777	2293	4484

Notes: Average values are reported on the characteristics of fathers-in-law in our sample in 2005. This includes healthy and unhealthy fathers-in-law. Standard deviations are in parentheses.

Table 3.9: Summary Statistics of Matched Women

	Total Sample	*Death of Parent in law*	*Alive and co-residing Parents in law*
Age	27.61	27.46	27.76
	(5.996)	(5.716)	(6.257)
Education in years	5.43	5.51	5.34
	(4.622)	(4.413)	(4.818)
Family size	7.87	7.84	7.90
	(2.702)	(2.736)	(2.674)
Household Assets	11.87	11.72	12.01
	(5.508)	(5.361)	(5.650)
Urban	0.16	0.17	0.15
	(0.363)	(0.373)	(0.354)
Number of Observations	544	272	272

Notes: Average values are reported on the characteristics of matched women in our sample in 2005. These women co-reside with healthy parents-in-law in 2005. They are matched on age, education, family size, household assets and location in urban/rural areas. Standard deviations are in parentheses.