Technology, shocks, and labor response: A gendered perspective

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Abstract

Socio-economic transitions in many developing countries have failed to enhance the labor force participation of women. This thesis examines the interaction between supply and demand-side factors of workforce participation from a gender perspective. First, it implements a cluster RCT to understand how access to a digital job matching technology that reduces job search costs impacts the labor market outcomes and harnesses the role of social networks. The findings highlight that while digital technology can increase the social acceptability of women working outside the home, the gendered structure of networks benefits men, and leads to conformation to prevalent social norms of home-based work by women to balance home production responsibilities. Second, the thesis examines the labor impacts of a negative production shock given the extant gender disparities in the labor market. The findings underscore that gender-neutral shocks can have gendered impacts, especially if social norms constrain women's access to coping mechanisms. Finally, it explores the role of social safety nets in mitigating the adverse effects of such labor market shocks. The results suggest that employment guarantee programs can protect livelihoods, but for certain demographic groups relatively more than others, depending on the nature and skill level of work offered.

Chapter 1

Introduction

1.1 Motivation

In contrast to the dramatic rise in female labour force participation rates (FLPR) ensuing from structural changes in developed countries (Goldin, 2006), FLPR in many developing countries continues to remain low and stagnant. India, for instance, has experienced rapid fertility transition accompanied by higher educational attainment by women (Census of India 2001 and 2011) since the early 1990s. However, these socio-economic transitions have not increased FLFP, as only 25% of India's women are in the labor force (PLFS, 2019; UN, 2013). A woman's access to employment is an important determinant of her intra-household decision-making power and control over resources (Sangwan and Kumar, 2021; Hoddinott and Haddad, 1995) with significant implications for household welfare. Not only has women's LFP remained stagnant over the last few decades in urban areas, it has declined in rural India. This puzzling trend has generated significant research to understand the determinants of female LFP and the persistence of gender gaps in the labor market.

The existing literature has extensively studied the supply side factors - mobility restrictions due to social norms (MacDonald, 1999), safety concerns (Field and Vyborny (2022); Dean and Jayachandran (2019); Chakraborty et al. (2018); Eswaran et al. (2013) and the burden of home production (Afridi et al., 2019)) - as constraints to the labor market participation of women. But much less is known about the demand side factors. The low market returns to women's work, along with a lack of 'good' jobs (Afridi et al., 2018), can contribute to the low levels of women's labor force participation in developing countries. Thus both supply and demand side factors can constrain women's labor market participation.

This thesis examines the interaction between supply and demand-side factors of workforce participation from a gender perspective. It assesses whether lowering job search costs and harnessing social networks can stem social constraints to women's employment. Specifically, it explores the potential role of digital technology in ameliorating the employer-employee matching frictions in the labor market. Next, it studies the labor impacts of production shocks given the extant gender disparities in the labor market. Gender-neutral shocks can have gendered impacts, especially if social norms constrain women's access to coping mechanisms. Finally, it examines the role of social safety nets in mitigating the adverse effects of such labor market shocks.

This thesis is divided into four chapters. Chapter 1 is introductory and provides a synopsis of the thesis. In Chapter 2, we implemented a cluster-RCT in the National Capital of Delhi to understand how lowering job search costs and harnessing social networks can stem social constraints to women's employment.[1] Chapter 3 uses high-frequency individual panel data to examine the gendered responses to production shocks in agriculture.[2] Chapter 4 explores the potential role of state capacity in ameliorating the impact of labor market shocks.[3]. The fifth chapter concludes and makes policy recommendations.

The following sections provide an overview of the research questions, methodology employed and the headline results from the subsequent chapters.

1.2 Job Search Technology, Social Networks, and Gender: Experimental Evidence from Urban India

Digital labor market platforms considerably reduce job search costs and matching frictions in the labor market (Banerjee and Chiplunkar, 2022). It has the potential to improve employer-employee matches, especially for women facing high job search costs due to their restricted

[1]This chapter is joint work with Farzana Afridi (Indian Statistical Institute, Delhi), Amrita Dhillon (King's College London), and Sanchari Roy (King's College London)

[2]This chapter is joint work with Farzana Afridi (Indian Statistical Institute, Delhi) and Kanika Mahajan (Ashoka University, India); the published version is available at Labour Economics or refer to Afridi et al. (2022b)

[3]This chapter is joint work with Farzana Afridi (Indian Statistical Institute, Delhi) and Kanika Mahajan (Ashoka University, India); the published version is available at Oxford Open Economics or refer to Afridi et al. (2022a)

mobility and lack of access to weak ties (Calvo-Armengol and Jackson, 2004; Mortensen and Vishwanath, 1994). However, these benefits may not be gender-neutral - social norms (Field et al., 2016a,b), along with gendered job preferences, can impact the labor market outcomes of women differentially, particularly when household decisions are made jointly by husbands and wives (Lowe and McKelway, 2019).

We implement a cluster RCT in the low-income neighborhoods in Delhi, India, which offers access to a hyper-local job aggregator platform. We offer this new job search technology in two treatment arms - (1) to matched husband-wife pairs to study the interplay of intra-household factors and (2) to husband-wife pairs and two of the wife's self-recommended peers to harness the role of networks in the adoption of technology and the labor market outcomes. And no offer is made in the control group.

One year after the intervention, the probability of the husband working increased by 4.7%, workdays (per week) by 55.2%, and the hours worked (per day) by 58.5% in T2 (treatment with wife's peer). Consequently, husbands' monthly earnings doubled in T2. While women's overall work status and earnings did not improve, the proportion of women who report being self-employed increased by 37.5% in T2 after a year. We find no positive effects on either gender in T1. Our results indicate significant network effects as the labor market participation, work intensity and earnings of husbands are higher in the network treatment arm compared to the only husband-wife pair treatment, relative to the control group.

Therefore, increasing access to job information by including networks can improve women's work opportunities theoretically. However, men are more likely to take advantage of information flows to improve earnings due to the gendered structure of the network, while women conform to the gender norm of working close to home & the bread-winner norm. These findings highlight the role of gendered social networks and social norms in producing gender-differentiated effects of new technology on labor market outcomes. While social networks play a role in the adoption of new technology, they do not always act as enablers in labor markets, especially for women may also lead to conformation to prevalent social norms of women working closer to home or taking up more flexible jobs to balance home production responsibilities.

In summary, reducing job search costs for women through digital technology can increase the social acceptability of women working outside the home. But attempts to boost women's employment and earnings may be futile if restrictive social norms continue to dictate their work choices.

1.3 The Gendered Effects of Droughts: Production Shocks and Labor Response in Agriculture

Climate change has increased the frequency of extreme weather events, including droughts, which are predicted to rise further if climate change continues unabated (World Bank 2013). This leads to greater production risks in agriculture as more than 75% of the world's cropped area still depends on rain. This is a serious cause of concern, as agricultural systems are managed by some of the poorest communities that lack access to coping mechanisms. It will adversely impact the significant proportion of the workforce whose livelihoods are supported by agriculture.[4] Men may be better placed to take advantage of available coping mechanisms and adjust to the shocks (Heath and Mobarak, 2015; Andrabi et al., 2013). But much less is known about gender differences in labor responses. Additionally, the impact of productivity shocks in agriculture can potentially exacerbate the extant gender differences in labor market outcomes when women's access to off-farm work opportunities is constrained by social norms that restrict their physical mobility.

Using unique individual-level panel data that captures seasonal labor inputs during 2010-14 across 8 agro-climatic zones of India to understand the labor impacts of negative productivity shocks. The detailed data allows us to study individual-level labor response across the farm and non-farm sectors to adverse productivity shocks, accounting for unobservable heterogeneity in their characteristics. This Chapter examines if droughts have gender-differentiated labor impacts and also explores the mechanisms underlying the gender-differentiated impacts on employment.

We find that women are 7.1% less likely to be employed than men but 80% more likely to seek work in a drought year. Men offset the effect of drought by diversifying to the non-farm sector. Men take up work outside the village and migrate during a drought but there is no impact on women's workplace location. Consequently, women are unable to cope with the adverse agricultural productivity shock. They either drop out of the labor force entirely or continue working in the low-productivity and high-risk farm sector. These gender-differentiated impacts are not driven by a skill deficit as men are diversifying into unskilled non-farm jobs.

We find suggestive evidence that women's access to non-farm work opportunities is constrained by social costs emanating from gender norms of home production and women's sexual purity. Younger women and women with young children work significantly lower non-farm days,

[4] For instance, 40% of the workforce in India depends on agriculture.

relative to older women and those without kids, by 14.6% and 21.4% respectively, when faced with a drought shock. Our proposed mechanism of restricted mobility is further validated by the finding that the provision of employment close to home helps women cope with negative income shocks disproportionately more than men.

Therefore, persistent extreme weather events due to climate change may exacerbate existing gender inequities in the labor market. Policy interventions that mitigate production risks in agriculture with a gender focus, e.g. job guarantees (NREGA), can help women cope with such shocks.

1.4 Employment Guaranteed? Social Protection During a Pandemic

The Covid-19 pandemic, an unprecedented health and economic shock to the world, highlighted the potential of social protection programs in mitigating labor market shocks. Extensive research on the pandemic suggested that economic impacts differ across demographic groups (Deshpande (2020), Dhingra and Machin (2020)). Social safety nets as policy tools are once again being debated. Limited evidence on both the role played by social safety nets in stemming labor market disruptions as well as their impacts across population groups.

Using nationwide, individual-level panel data with over a million observations from January 2019 - August 2020, we first examine the labor market impacts of the nationwide lockdown in India that was introduced to contain the spread of the pandemic – overall and dynamic phase-wise effects as mobility restrictions were gradually eased. We employ a difference-in-differences (DID) estimation strategy that compares changes in general employment status pre (2019) and post (2020) pandemic, during January-March (control months) and April-August (treated months). Next, we assess the role of India's employment guarantee program (MG-NREGA) in cushioning job losses ensuing from the pandemic. As contemporaneous work generation is endogenous, we use historical data on employment generation under MG-NREGA in a district over five years, from 2014-18, to measure the capacity of the state to provide social protection under the scheme during this crisis.

We find a large negative shock to employment due to the pandemic. These job losses were similar across the rural and urban regions but were more pronounced for men as they engage more with the labor market relative to women.

Our findings indicate that regions with higher historical state capacity to provide public work under the scheme were able to cushion job losses significantly in rural areas during the pandemic. Consequently, an increase in state capacity by one MG-NREGA workday per rural inhabitant in a district reduced job losses in rural areas in April-August 2020 by 7% overall over the baseline employment rate. As found in Chapter 3, the cushioning was significantly more pronounced for rural women. The marginal effect of an increase in average historical person-days under MG-NREGA by one day per rural inhabitant increased the probability of employment for women by 74% over the baseline employment rate post the lockdown. Consistent with the role of women's jobs as insurance (Sabarwal et al., 2011) and the counter-cyclicality of women's labor force participation in developing countries (Bhalotra and Umana-Aponte, 2010), not only were employment losses for women stemmed, but women who were previously not in the labor force also entered the labor market during the crisis in high state capacity districts.

This greater benefit of MG-NREGA accruing to women is supported by their stated job preferences in Chapter 2. Women prefer jobs near home due to mobility restrictions, safety concerns, and the need to balance care work with market work (Fletcher et al., 2019) as well as a guaranteed job (Dhingra and Machin, 2020). Since MG-NREGA guarantees work within the village precincts it meets the 'desired' job characteristics of women. Furthermore, the gains from the program were greater for the relatively more mobility-constrained women - married or with young children care responsibilities. Our results suggest that employment guarantee programs can protect livelihoods, but for certain demographic groups relatively more than others depending on the nature and skill level of work offered. There were no spillovers of the employment guarantee scheme on urban employment, highlighting the need for complementary policies in urban areas.

Chapter 2

Social Networks, Gender Norms and Women's Labor Supply: Experimental Evidence Using a Job Search Platform[1]

2.1 Introduction

Women's employment in many developing countries still lags behind that in most developed nations (Klasen, 2019). Peer effects have been shown to increase female labor force participation in many developed countries via social learning (Nicoletti et al., 2018; Maurin and Moschion, 2009; Mota et al., 2016) and conformism (Cavapozzi et al., 2021). However, it is less clear whether these findings generalize to developing countries, where social norms restricting women's mobility and outside interactions often play an important role in constraining female labor force participation (Jayachandran, 2021). In particular, little is known about whether women's networks can be harnessed to improve their participation in the labor market in low income settings, and specifically in work outside the home to increase women's agency (Anderson and Eswaran, 2009).

[1]This paper is a joint work with Farzana Afridi (ISI-Delhi), Amrita Dhillon (King's College, London) and Sanchari Roy (King's College, London).

In this paper, we provide the first causal evidence on this question by using a cluster randomized control trial to evaluate an intervention that offered access to a digital job search platform in Delhi, India. The platform provided hyperlocal employer-employee matching and job aggregator service to blue-collar workers, and aimed to lower job search costs. In the first treatment arm, the service was offered free of charge to a randomly selected group of married couples (non-network treatment).[2] In the second treatment arm, the service was offered to married couples *and* the wife's peer network (network treatment), also free of charge, in order to disentangle the network effect. Neither couples nor their network were offered the service in the control group.

A little over one year after the intervention, we find no significant impact on women's likelihood of working in the network treatment group relative to the control group, although the point estimate is significantly higher than in the non-network treatment group (p=0.02). Instead, we find a significant improvement in their *husbands'* labor market outcomes, both at the extensive and intensive margins. In particular, husbands' likelihood of working increased by 4.6%, while their workdays (per month) and the hours of work (per day) went up by 8.36% and 8.11%, respectively, compared to the control group. As a result, husbands' monthly earnings more than doubled in the network treatment group relative to the control group. There is an imprecise increase in the workdays (per month) of husbands in the non-treatment arm by 6.76%. We do not find any positive impact on labor market outcomes of either husbands or wives in the non-network treatment group.

We argue that the explanation for the unexpected positive finding on husbands', but not wives', employment in the network treatment group lies in the gendered structure of social networks in our setting. Consistent with existing evidence (Afridi et al., 2021; Kandpal and Baylis, 2019), we document women's networks as being significantly more family-centric and home-bound compared to men's. In particular, 96% of the average wife's network in our sample consists of non co-resident family members or neighbours, as opposed to 56% for her husband. In addition, we also document significant overlap between wives' peers and those of their husbands', including relatives who constitute over half of a wife's network on average. Such a gendered structure of social networks in our setting implies that in the network treatment group, men (and husbands) benefited more than women from the diffusion of information about job opportunities from the digital platform within the network (Beaman and Magruder, 2012; Caria

[2] The service was offered to both husband and wife to enable full information-sharing within the household in a setting where joint household decision-making about labor market decisions is the norm (Bernhardt et al., 2018; Conlon et al., 2021).

et al., 2020). This is further confirmed by our findings that only the male peers in the wives' networks experienced a significant improvement in employment outcomes, and that husbands with greater network overlap with their wives benefited more.

In contrast, we find that self-employment among wives in the network treatment group increased by 40.9% increase compared to the control group. At the same time, proportion of women engaged in daily wage work in this group declined though insignificantly, suggesting a degree of substitution away from precarious work to self-employment. We argue that this observed impact on women can be attributed to conformism to gender norms, which is consistent with the high preference for home-based work for women (over 80%) and strong support for male bread-winner norm reported by both husbands and wives at baseline. Consequently, while husbands in the network treatment group took advantage of greater access to information on job openings on the digital platform, their wives stayed away from paid, outside work and took up home-based work instead, such as tailoring.[3] Thus, harnessing women's peer networks to improve their labor market participation may backfire if the nature of their networks reinforce (conservative) gender norms about women's (outside) work. This is the key contribution of our paper. In addition, it is consistent with our finding that while treatment (both with and without network) attenuated attitudes towards regressive gender roles, it failed to amplify attitudes around women's work that were progressive, thereby pointing to the stickiness of such norms and the inherent challenges faced in changing them.

We rule out several alternative explanations for the differential employment treatment effects by gender. One such explanation for the null effects for wives' employment could be that women are less likely to have access to or use new digital technology. However, we do not find any gender differences in the take-up of the new technology. Moreover, as hypothesized, the probability of being registered on the job portal was higher for women whose peers also registered. Hence, adoption of new technology is indeed more likely when peers also adopt the same technology. Another concern could be low overall demand for women's labor, especially if recovery from job losses due to the Covid-19 pandemic that unfolded during our study, was unequal by gender. However, we find that overall, wives received job offers from the portal at a similar rate to their husbands. Further, overall post-pandemic female employment had started to recover in Delhi during the time of our study, indicating the potential of digital job

[3]This finding is consistent with recent evidence summarized in Bandiera et al. (2022), who conduct a meta-analysis using a large cross-section of countries to document that poor women are often the last to get access to wage jobs, behind men.

search platforms to further boost demand for women's labor at this time. Similarly, the positive employment effect for husbands does not appear to be driven by pandemic-induced job losses that occurred immediately after our intervention. We find no differential impact on husbands' employment outcomes in the network treatment group either by job loss during the pandemic or work status right after the pandemic-induced lockdown.

Our paper makes two contributions. First, we contribute to the rich literature on the role of peer effects in driving various economic outcomes in developing countries, including agricultural technology adoption (Beaman et al., 2021; BenYishay and Mobarak, 2019), microfinance (Banerjee et al., 2013) and migration (Munshi, 2020). Particularly for women, existing studies have documented positive peer effects on entrepreneurial activity (Field et al., 2016a), family planning and contraception (Anukriti et al., 2022), and autonomy (Kandpal and Baylis, 2019). We advance this literature to the labor market by experimentally testing whether peer effects can be leveraged to increase female employment in a setting where it is stubbornly low, such as India. Contrasted to the existing studies that highlight the positive role of women's networks (even when relatively thin), our paper shows that the actual structure of women's networks plays a key role in mediating peer effects. In our setting, where constraints on women's physical and social mobility lead to their network structure being disproportionately made up of kin and neighborhood ties, the gendered structure of social networks may further disadvantage women in the labor market.[4] This may be especially true for low-income urban women in developing countries, many of whom migrate to cities post-marriage and consequently lose their natal links.[5] Hence, our paper also extends our understanding of the salience of women's peer effects in urban and blue-collar contexts, beyond the primarily rural settings in existing research on women's economic engagement in low-income countries.

Second, our paper also ties into the literature on labor market frictions that differentially impede women's labor force participation by focusing on a hyperlocal, app-based matching platform.[6] Restrictions on women's mobility and outside interactions, often rooted in social

[4]Constraints on women's physical and social mobility lead to a large proportion of women's networks consisting of kin and neighborhood ties, and few weak ties (Stoloff et al., 1999). While such a network structure provides social support (Wellman and Wortley, 1990), it may not be advantageous in improving labor market outcomes, for which weak-ties are critical (Calvo-Armengol and Jackson, 2004; Mortensen and Vishwanath, 1994).

[5]Using out-migration data from the nationally-representative National Sample Survey (NSS), we find that over 30% of the overall rural-to-urban migration in India is accounted for by marriage alone, and women constitute about 44% of such migrants. Similarly, 61% of women who migrate from rural to urban areas report marriage as the reason. Furthermore, women's safety concerns may be higher in cities relative to villages. As per the National Crime Records Bureau (NCRB) 2009 data: 383 crimes (per million women) against women were reported in Delhi's districts while the national average was 202 per million women.

[6]Women exhibit limited physical mobility stemming from social norms (MacDonald, 1999), safety concerns

norms, may lower their awareness and information about economic opportunities compared to men in entrepreneurial work (Field et al. (2010) and white-collar jobs (Lindenlaub and Prummer, 2021), leading to fewer weak ties (Calvo-Armengol and Jackson, 2004; Mortensen and Vishwanath, 1994), higher job search costs and hence lower employment. Digital labor market platforms can offer a potential solution to level the "gender playing field" in this context (Agrawal et al., 2015). In contrast to the emerging literature that has found little impact of job matching services on employment (Kelley et al., 2022; Jones and Sen, 2022; Dhia et al., 2022),[7] our paper shows that harnessing social networks may not only increase the take-up of digital job search platforms but also improve employment opportunities and earnings. However, the challenge of improving women's labor market outcomes may not be overcome through adoption of new technology via peers alone, particularly in low-income settings with strong gender norms around women's labor allocation. Thus the benefits of such technology may not be gender-neutral, particularly when household decisions are made jointly by husbands and wives.

The paper is organized as follows. Section 2.2 outlines the sample, intervention and experimental design. Section 2.3 discusses the data and summary statistics, along with the estimation methodology. The main results are presented in Section 2.4, while we discuss mechanisms that can explain our findings in Section 2.5. Section 2.6 concludes.

2.2 Intervention, Sample and Experimental Design

2.2.1 Intervention: Job search platform

Since the objective of our study is to improve women's labor market engagement, we partnered with a job-matching platform that is geared towards women called HelpersNearMe. It is a hyperlocal app-based job aggregation platform that connects potential employers directly with nearby blue-collar workers for permanent or temporary hiring, much like Uber for taxi services. Workers register on the platform, where they provide information on previous work experiences and their job preferences (including preferred distance to work and expected wages). This information then allows the platform to match registered workers with potential employers

(Dean and Jayachandran (2019); Chakraborty et al. (2018); Eswaran et al. (2013)) and the disproportionate burden of home production (Afridi et al., 2019). As a consequence, relative to men, women may have higher job search costs and prefer work closer to home. Thus hyper local labor market platforms can theoretically benefit women more.

[7] Wheeler et al. (2022) is a notable exception, finding positive employment effects of LinkedIn platform. Note that, unlike our intervention, none of these papers study platforms that provide hyperlocal, app based job search aggregator services or the blue-collar segment of the labor market.

who are looking for candidates for specific job profiles based on their search preferences (e.g. location, type of work, tenure i.e. short-term gigs or long-term contracts, wage offer etc.). The employer can then call the matched worker on their registered phone number with the job offer. Thus, registered workers are mostly passive on the platform - they cannot reach out to potential employers via the platform, but wait to receive job offers from employers over phone. The platform records job offers that are accepted but not those that are rejected.

Employers pay an upfront service charge to the platform. No payments are required of the worker for a successful match. There is a minimal expense of 100 INR per person (equivalent to 20-30% of average daily earnings) for platform registration to meet the cost of verification of worker identity. For our treated participants, this registration fee was paid for by the research project. Since workers may connect with many potential nearby employers without physically looking for work or any intermediaries or job contractors, this technology potentially reduces job search costs significantly (for both ends of the market). Furthermore, the worker can accept a job offer as per their preferences, including location and wage.

The platform is unique in catering to the potential constraints of blue collar workers, particularly women. First, the platform does not require smartphone ownership by these low-income individuals (unlike most other job matching portals). A feature phone is sufficient to receive calls from matched potential employers. This lowers barriers to entry into blue collar jobs, especially for women who are less likely to own smartphones. Second, the platform matches workers to employers hyperlocally. Hence workers can find jobs closer to home, which we show later is preferred by women in our sample. Given these features, it is not surprising that overall in 2019-20, women made up 70% of all workers registered on the platform, 86% of workers deemed suitable for a given job (86%) and 87% of workers who received a call from an employer for a job. We provide more details about the gender composition of registered individuals and the types of work offered on the platform in Appendix Table 2A.1.

2.2.2 Sample

Our experiment is set in low-income neighbourhoods of the National Capital Region of Delhi, India, where HelpersNearMe operates. Delhi is an urban center with a relatively young population: over 52% are in the 18-45 age group (Periodic Labor Force Surveys (PLFS) 2018-19), a majority of whom are married (73% of women and 56% of men). Female labor force participation in urban India is dismally low, 16.73% vs. 93.85% for men, and even lower in Delhi that the national average (by 8.98%) despite higher years of formal education than the national average (PLFS, 2018-19).

We use publicly available household listing from electoral registers as the basis of our sampling frame. Delhi has over 300 Electoral Board (EB) wards contained in 70 Assembly Constituencies (AC) across 11 districts. EB wards with a significant proportion of slum clusters (low-income residential areas) resettled into permanent habitations were considered for sampling and mapped into relevant Census 2011 wards to assess their population, employment, literacy, and civic amenities. We sampled 24 such EB wards spread across 11 ACs within 5 districts of Delhi - West, North, North-west, Shahadra, and North-east. On average, an AC consists of around 150-180 polling stations (PS), with approx. 500-1000 eligible voters (or 250-500 households) per PS. For each of the 11 sampled AC, a stratified random sample of about 10 PS was drawn, and within each sampled PS, 15 households were randomly sampled for inclusion in our study.[8] A household was considered eligible for the study if it had at least one married couple in the age group of 18-45 years. These individuals were likely to be engaged in the labor force, and women are more likely to have home production responsibilities, including child care.

2.2.3 Experimental Design

Figure 2.1 shows the geographical spread across Delhi of the sampled 108 polling stations, which form our primary sampling unit (cluster). The average distance (straight-line) between any pair of polling stations in 10.6 kms. To minimise the risk of contamination, the polling station was chosen as the unit of randomization in our cluster RCT design. The sampled 108 polling stations were randomly assigned to one of three arms, with 36 clusters each: the non-network treatment arm (T1), the network treatment arm (T2) and control (C).

In the non-network treatment arm, we visited the sampled households to provide information about the job search platform to the woman and her husband, separately. The reason for offering the treatment to both the wife and husband, instead of just the wife, is that female labour supply decisions in this setting are typically jointly taken. We provided detailed information on how the job matching platform works, the registration process, and its potential benefits in obtaining work to each respondent. This was followed by showing a testimonial video, tailored to the gender of the respondent, that we developed with beneficiaries of the platform. Thereafter, we offered to

[8] Stratification of PS was by proportion of low-income residential habitations. To ensure sufficient power in the event of attrition and replace households where both husband and wife could not be interviewed, we randomly sampled additional households beyond our target sample size.

register the respondent (both the woman and her husband) on the job-matching platform at no cost. By design, the couple was aware of each other's platform registration offer and registration decision.

In the network treatment arm (T2) the same procedure was followed as in T1, but afterwards, we also offered to register up to two of the wife's peers in her network for this service. The platform's registration cost for peers in T2 was also covered by the research project. In the control group (C) we did not offer to register the respondents or their network to the job-matching platform.

While the registration offers were made in person to the couples, in the network treatment the peers selected by the wife from her social network were offered the platform registration over phone during intervention.[9] If the wife suggested names that were not in their top two rank-ordered baseline network list, these new peers were also surveyed and offered platform registration. Once an individual expressed interest in registering (in either treatment group) we passed on their ID and mobile phone number to the job-matching platform, which would then follow up with a phone call to verify details and formally register the job preferences of the individual within 24 hours (the process of 'on-boarding').

Of the individuals offered treatment, husbands and wives showed comparable interest in registering (70% of husbands and 65% of wives). The proportion of wives who showed interest was similar in both treatments (about 64%), while husbands in T1 showed slightly greater interest (73% vs. 66%). Conditional on interest, 37% successfully registered on the portal. The registration rates are higher in the network treatment arm (40%) in contrast to the non-network treatment arm (34%), and for both husbands and wives. Amongst the wives' peers who were offered registration the proportion interested and registered (conditional on interest) was 72% and 47%, respectively. The final (unconditional on interest) registration rate was lower at 25% (overall) and marginally higher for husbands in both arms (network - 28% husbands & 25% wives; non-network - 26% husbands and 22% wives). See Appendix Table 2A.2 for further details.

[9] Besides individuals declining to formally register after showing interest, registrations could also fail due to verification issues at the platform's end. Note that it is entirely possible that respondents in T1 could inform their peers about the platform. However, any cost of registration would then be borne by the peer, in addition to the main respondent bearing the cost of effort in initiating conversations within her network about the portal, which can be especially high in contexts where working from home is the norm for women. Not surprisingly, only 4% of non-treated peers report being informed about the platform by their friends/relatives and of these only 0.07% registered on the platform (data from both survey and platform). Of the treated peers almost all (98%) were informed about the portal by the research team.

2.3 Data, Summary Statistics and Estimation

2.3.1 Data

Our baseline survey was conducted in May-July 2019 at two levels: (a) household, and (b) individual. The household survey collected information on the demographic composition of the household and other socio-economic characteristics (e.g. assets, migration status, and other details from the household head). The information on household members was utilized to identify the currently married (and cohabitating) couples in the household for the individual survey. If there were multiple couples in the 18-45 age group, we selected the couple with the youngest wife, since they are likely to face tighter time constraints as well as higher labor market trade-offs with domestic and childcare work.

The individual survey was conducted separately (and in privacy) with the husband and the wife to obtain information on their education, work history, work preferences, gender norms, and attitudes towards women's labor force participation. In addition, we elicited information on the individual's social network through a name generator process using contextual/situational references.[10]

Following the name-generating process, the respondents were asked to rank the top four peers from their list of names in order of their self-perceived proximity/closeness with these individuals. We also collected data on the nature and the intensity of the relationship with the people in the network to understand how the link was formed and how frequently they interact with the people in their network, respectively.[11] Mobile numbers to contact these four peers were recorded. We then conducted a phone survey of up to two of these four peers, moving down the list in rank order (conditional on mobile number availability). For up to two peers, therefore, we gathered detailed information on gender, age, own work history, as well as, gender norms and attitudes.

[10]The main respondents were asked to name non-co-resident individuals that they most often interacted with under the following situations - (1) Emergencies: "Borrowing from in case of emergency; for example, if you immediately need 400-500 rupees for a day and there is no one else at home you could borrow from?", "In case of medical emergency when you need to call someone immediately to rush to the doctor/hospital and there is no one else at home", "In your neighborhood if you have to immediately borrow food items like rice, tea, sugar, cooking fuel, etc, who would you go to?"; (2) Social activities: "Going for a walk/to the park and chatting with in free time", "Shopping or going to local market with, for example, to buy vegetables or ration?", "Attending social functions or festivals or going to religious places with; for example going to the temple/mosque or participating in group prayer in the colony or meeting during Diwali or Chhat Puja (festivals) celebrations etc?"; and (3) Workplace interactions: "Having lunch at work or spending your free time at work with; for example chatting or having tea while taking a break", "Travelling to work with".

[11]Respondents were asked about the typical frequency of interaction (e.g. daily, 4-6 times a week, or once a week) with their peers, both in person and over the phone.

To measure the impact of the intervention on the respondents' and the treated peers' work status, we conducted two follow-up surveys. Endline 1 was conducted approximately 6 months after the intervention (Aug-Nov 2020) while Endline 2 was conducted about 14 months after the intervention (Apr-June 2021). At both endlines, we resurveyed the main respondents as well as their peers in the network (including any new peers at intervention). We also obtained data from the job-matching platform on the sample of registered respondents' (main respondents and peers) reported job preferences and other details recorded at the time of registration, as well as job offers and acceptances from the date of registration until June 2021. However, platform data on job offers was incomplete as it only recorded whether a match took place or not, i.e. accepted offers. Hence we also collected detailed self-reported data on job offers (accepted or not) during both endline surveys. The timeline of the study is summarized in Table 2.1.[12]

Our original sample consisted of 3,127 individuals (1,543 husbands and 1,584 wives) from 1,613 households across 108 polling stations, as shown in Table 2.1. In the follow-up surveys, the attrition rate was below 5% of the baseline sample - 1.85% at Endline 1 and 4.67% at Endline 2. Throughout our analysis, we restrict the data to matched husband-wife pairs interviewed at baseline, i.e. 1,514 couples.[13] With the matching restriction, attrition remains below 5% - 98.28% of the couples from baseline were followed-up at Endline 1 and 95.48% at Endline 2.

As mentioned previously, up to two peers of the main respondents were also contacted by phone. At baseline, a total of 3,468 peers were surveyed (of 2,331 main respondents who were able to provide mobile number of their peers). Recall that at intervention women respondents were asked to suggest two peers who they would like to be offered registration on the job matching platform in the T2 arm. Some of these peers were not in the baseline network. In the follow-up survey rounds, we thus interviewed both baseline and any additional peers treated at intervention - 3,583 of the 4,208 (=3,468 + 740) peers at Endline 1 and 3,522 at Endline 2. A loss of connection over the phone with the peers was the primary reason for attrition of 14.85% at Endline 1 and 16.3% at Endline 2.

Throughout, we report results 14 months after intervention, i.e. at Endline 2. We find

[12]Our study coincided with the pandemic-induced stringent national lockdown in India which began on March 24 2020, and eased by August 2020. Our baseline survey of couples was conducted in person but due to onset of the pandemic, we switched to phone interviews thereafter. Our first endline in August-November 2020 was conducted entirely over the phone. The second endline survey began on April 2, 2021, with in-person interviews of almost 50% of our sample. However, given the devastating second wave of the pandemic in India, when cases surged from mid-April 2021, we switched to phone interviews from the end of April until the end of the survey round in June 2021.

[13]99 individuals out of the original sample of 3,127 were unmatched to their spouse and hence dropped.

insignificant treatment effects 6 months after intervention (Endline 1), discussed later, which is attributable to the economic shut-down during the pandemic.[14]

2.3.2 Summary statistics

Table 2.2 defines and summarizes the key variables of interest for our matched husband-wife sample at baseline. Panel A shows the household characteristics. The average household size is slightly over 5 with 19% living with multiple generations (joint family) and about 57% having a child below the age of five years. A majority of households are Hindu (82%) and over 40% of the households belong to the socio-economically disadvantaged SC-ST group. Nearly two-third of these households are migrant families from outside Delhi, but have lived at the current location for over 28 years on average.

Panel B presents the individual characteristics of the main respondents, i.e. the couple, in our sample. They are relatively young (32.7 years), with some education (over 60% have above primary level of education) and high usage (94%) of mobile phones. Overall, 60% of them are working (irrespective of gender), out of which 16% are engaged in casual labor, 21% are self-employed and 22% have salaried jobs in government and private institutions.[15] Unemployment rate is low at 3%, while 38% of the sample is not looking for work i.e., not in the labor force.[16] The average individual earnings was 6,028 (10,793) INR per month unconditional (conditional) on work status. Finally, Panel C summarizes the characteristics of two rank-ordered peers listed at baseline. These peers are comparable in age, education, and work status to the main respondents.

The treatment and control groups are broadly balanced in terms of household characteristics (Appendix Table 2A.3) as well as individual characteristics for both husbands and wives (Appendix Table 2A.4), apart from marginal differences in unemployment rates. Our main specifications will include this and other baseline characteristics to account for such chance differences between treatment groups.

[14]The pandemic severely disrupted economic activity almost immediately following our intervention in 2020. India's GDP contracted by 23.9% during April-June and 7.5% in the second quarter (July-September) of the 2020-21 fiscal year as opposed to 4.2% GDP growth in 2019-20. Not surprisingly, unemployment peaked at 18.5% in the first quarter of 2020 but started to taper off from the second quarter onwards (7.5% in both July-September and October-December 2020), as demand recovered (Unemployment Rate in India, CMIE). Economic activity picked up post easing of the nation-wide lockdown in August 2020.

[15]These labor market participation rates are based on reported main activity over the previous year at baseline.

[16]While the unemployment rate is comparable, the labor force participation rates in our sample are 5-6% higher than the average for Delhi aligning with our sample's close location to industrial areas. This suggests that our estimated treatment effects may be a lower bound on the effect of job-matching platforms.

2.3.3 Gender differences

We also document significant gender differences in key sets of baseline characteristics that relevant to our study: labour market participation, social network structure and social norms and preferences.

Labor market participation: The gender differences in the overall labor force participation variables are shown in Panel A of Table 2.3. We find significant differences in the work characteristics of husbands and wives at baseline. Wives are 72 pp less likely to be working in the reference period than their husbands. While husbands are mostly engaged in salaried jobs, among the wives who are working, a majority are self-employed. More strikingly, $3/4^{ths}$ of the wives are not in the labor force, i.e. they are neither working nor actively looking for work. Not surprisingly, husbands earn more than ten times the average earnings of wives (unconditional on work status). Conditional on working, the average earnings of husbands and their wives were about 12,300 INR and 4,500 INR, respectively.

We observe a bigger mismatch between expected and actual earned wages of wives compared to their husbands among our sample that registered on the job aggregator platform. Wives who registered on the platform expected an average salary of around 10,500 INR (133% higher than the average baseline earnings of women who work), while husbands expected 13,300 INR or 8% higher than their average baseline earnings. This mismatch between expected and actual earnings persist even after accounting for differences in occupational preferences and baseline occupation types of men and women, suggesting either women's lack of labor market information or higher reservation wage or both. Data from registrations on the job matching platform show that women preferred service sector jobs (75% - e.g. beautician, telecaller), providing domestic help and care services (65% - cooking, babysitting, and other care jobs), and also work within a 3 km distance from their homes, on average. In contrast, men registered for a larger number of job profiles (service sector jobs (60% - delivery boy, office helper, and salesman), factory and manufacturing jobs (23% - machine operator and technicians), domestic help and services (27% - driver, peon), and construction work (10%)). They were willing to travel more than double the distance (6.6 km) preferred by women.

Social network structure: We observe sharp gender differences in the social network structures reported in Panel B of Table 2.3. First, wives' social networks are significantly more family-centric and home-bound compared to their husbands'. 96% of wives' peer networks are made up of non-coresident relatives and neighbors compared to just 56% for husbands. The narrowness of wives' networks is also reflected in a negligible proportion of them reporting any friends (defined as not a relative or neighbour) as their peers, in contrast to their husbands (4% versus 44%), and no co-workers, which is not surprising as only a quarter of wives report to be working and hence have the opportunity of interacting with people outside their home sphere. Second, social networks are gender-homophilous. Nearly three-fourths of wives' peers are female, while more than 90% of their husbands' peers are male. The proportion of 12% for husbands is not consistent with the split in Table A.5 which indicates 7% Appendix Table 2A.5 presents further details on the composition of wives' and husbands' social networks. As Panel B reveals, on average, only around 20% of these female peers of wives are likely to be working in baseline, compared to 90% of their husbands' (overwhelmingly male) peers (Panel A). This structure of women's social network, which is likely to be less amenable to obtaining job information and referrals, intensified at intervention (Panel C).[17] The peers suggested for treatment by wives in T2 were more likely to be female (80%), younger (by about 3 years) with 5% lower average employment rate than peers reported at baseline. In addition, the home-bound structure continued to dominate - 85% of the treated peers were either non co-residing relatives (46%) or neighbors (39%).

Social norms and work preferences: Table 2.4, Panel A indicates a high prevalence of regressive attitudes towards women's work outside of home among both husbands and wives (asked in privacy). A vast majority of respondents support the view that women should be homemakers, men more than their wives. However, wives are more likely to believe they should support their husband's career than their own, and prioritize relationship with children over market work.

In Panel B, we summarize responses to progressive attitudes towards women's work outside the home. Wives are 6 pp more likely to agree that it is acceptable for women to work outside the home and 27 pp more likely to agree that married women should earn even if the husband provides support. However, only 33% of husbands approve of a married woman earning if she has a husband capable of supporting her, suggesting a strong male breadwinner norm. These norms and attitudes align with job preferences that women reported for themselves and what husbands approved of for their wives as shown in Panel C. Home-based jobs are considered the most suitable for women by both husbands (78%) and wives (81%), followed by salaried government or private sector work. Hence there is a preference for work that is flexible, requires limited mobility, yet is 'high status' for married women.[18] Note that only 2% of wives and 3%

[17]Put this footnote in table notes for Table A.5) 881 individuals (peers) were suggested by wives at intervention in T2, of which 153 had been surveyed at baseline.

[18]Using data on women working at baseline, we find that engagement in self-employment activities (e.g. family-

of husbands agree that women should not work, indicating demand for jobs for women.

2.3.4 Estimation

Our first specification combines both treatment arms (non-network and network) into a single indicator of treatment status that takes value 1 if the couple and/or the wife's peers in her network were offered to register with the job aggregator platform, and 0 otherwise. Thus, the baseline specification is:

$$Y_{iv} = \alpha + \beta T_v + \phi Y_{iv}^0 + X_{iv} +_{iv} \tag{2.1}$$

where Y_{iv} are measures of labor market outcomes of individual i in cluster v at endline. It includes work status, the number of days worked in a month, the number of hours worked in a day, monthly earnings (INR), and occupation category (casual labor, self-employed or salaried). Work status is a dummy variable that takes value 1 if an individual reports engagement in an occupation over the past 3 months and zero otherwise. The occupation categories are dummy variables constructed on the basis of the main occupation in the last quarter.[19]

T_v is a dummy indicating whether cluster v is randomly assigned to either treatment - without network (T1) or with network (T2), Y_{iv}^0 is the corresponding baseline labor market outcome of individual i in cluster v. X_{iv} are a set of baseline characteristics of individual i in cluster v that may affect their labor market outcomes. These include household characteristics (household asset index, dummy for joint family, number of under-5 children, dummy for SC/ST, dummy for Hindu, dummy for migrant status, years living in current location) and individual characteristics (education of the individual, age, occupation code, and mobile phone usage).[20]

Our second specification distinguishes between the two types of treatments to estimate and

run retail shops, tailoring) and casual labor is relatively less time intensive – 4.5 workdays compared to 6.5 workdays per week in a salaried job. Further, self-employment is typically undertaken within household premises or residential locality, while casual labor and salaried work entail travel to work. But while monthly earnings of self-employed women averaged 2,695 INR, those engaged in salaried and casual labor were earning 7,686 INR and 3,333 INR, respectively. Thus, higher flexibility of home-based work costs women almost three times the average monthly earnings they could earn in relatively less flexible salaried work.

[19]We first asked about the main activity of an individual over the last quarter from the time of the survey. Work status equals 1 if the respondent is engagement in casual labor, self-employment, or salaried work and 0 otherwise. For this reference period, we then asked days worked in a typical week, the average number of hours worked in a day, and the monthly earnings. For instance, monthly earnings reported 14 months after intervention record the average amount earned in a month from the main occupation since January 2021 (3 months from the survey in April 2021).

[20]The estimation strategy, including the list of control variables, is as per the pre-registered analysis plan. See Table 2.2 for details on the construction of the occupation and other variables, including the asset index.

compare their impact as follows:

$$Y_{iv} = \alpha + \beta^1 T_v^1 + \beta^2 T_v^2 + \phi Y_{iv}^0 + X_{iv} +_{iv} \tag{2.2}$$

where T_v^1 is a dummy variable indicating whether cluster v is assigned to the couple only registration treatment or not and T_v^2 is a dummy variable indicating whether cluster v is assigned to the couple plus the wife's network treatment or not. The control variables are the same as discussed above. In both specifications, the standard errors are clustered at the unit of treatment randomization, i.e. the polling station (PS).

We interpret the coefficients on the treatment variables as intention to treat (ITT) estimates. Our treatment potentially reduces job search costs by offering to register individuals on the job aggregator platform, as mentioned previously. Being assigned to either treatment may increase the probability of an individual finding a job due to the reduced job search costs if they register on the platform. These jobs are also likely to be better aligned with their work preferences, perhaps more so for women than men (as discussed previously) given the hyperlocal matching process. Therefore, we hypothesize that the offer of platform registration will improve the labor market outcomes of the individual both on the extensive and intensive margins (i.e. $\beta > 0$ in equation (3B.1)). The network treatment (T2), in addition to easing job search costs and improving employer-employee matching, also harnesses the wife's network.[21] Registration rates of main respondents (particularly wives) may be higher in T2 if people in one's network also register on the platform since it's a new and unknown technology and peers' adoption/non-adoption might signal whether it is potentially beneficial or not.[22] In addition, since up to two additional individuals (in the wife's network) are also offered the service, the quantum and flow of information on job openings is likely to be higher in T2 relative to T1, creating a multiplier effect. Hence, we expect the offer to register women's friends for the employment search service to have a relatively higher positive impact on labor market outcomes ($\beta_1 < \beta_2$ in equation 2.2) in T2.[23]

[21] We were successful in offering platform registration to at least one of the wife's peers via phone survey for 84% of the couples assigned to T2.

[22] Alternately, there could be competitive pressure to conform to peers. Either way, it predicts a higher technology adoption rate in T2 than in T1.

[23] While in the estimating model, we run separate analyses of the impact of our intervention on wives and their husbands, our experiment design accounts for joint decision-making through full disclosure of individual decisions, including the use of the aggregator service, which may mediate the impact of our intervention on woman's work-related outcomes.

2.4 Main results

2.4.1 Labor market participation

Table 2.5 reports ITT estimates of our intervention on the probability that an individual is working in the reference period, by gender, using the specifications described above. Columns (1)-(2) report the results using equation (3B.1) while columns (3)-(4) report it by treatment group as per equation (2.2).[24]

More than a year after the intervention, we find no significant overall treatment effect on either wives (column (1)) or husbands (column (2)). Separating by treatment type, we find no significant impact on wives' likelihood of working in the network treatment group relative to the control group, although the point estimate is significantly higher than in the non-network treatment group (p=0.02). In contrast, we find a significant improvement in their husbands' likelihood of working by 4.4 percentage points (pp) relative to the control group (equivalent to 4.6% of the baseline mean). Similar to their wives, the coefficient for husbands in the network treatment group is also significantly higher than that for their non-network treatment counterparts (p=0.00).[25]

Next, we examine the treatment effects on the intensive margin in Table 2.6, measured by the number of days worked in a month (Panel A) and the hours worked in a day (Panel B).[26]

Wives show no significant overall treatment effect on either dimension of intensive margin (Panels A and B, column (1)). However, disaggregating by treatment type, we note a marginal decline on both dimensions for wives (Panels A and B, column(3)) in the non-network treatment group (T1) but not in the network treatment group (T2).[27]

In contrast, we find positive treatment effects on the monthly workdays of husbands with no significant overall treatment effect on work hours (Panel A, column (2)). Husbands in both the treatment arms reported increased number of days worked in a month (Panel A, column(4)).

[24] Appendix Table 2A.6 shows insignificant effects 6 months after intervention (Endline 1), attributable to the economic shutdown during the pandemic.

[25] We also analyze the heterogeneity in these treatment effects by baseline demographic characteristics in Appendix Table 2A.7. We find no statistically significant difference in the outcomes of wives or husbands in the network treatment group by poverty status, caste, religion, education, and number of children aged 5 or below. We find that wives whose peers reported relatively progressive attitudes at baseline are more likely to be working relative to the control group (column (7), Appendix Table 2A.8).

[26] We also test for alternative log specifications - IHS transformation ($log(y) = log(y + (y^2 + 1)^{1/2}$) (Burbidge et al., 1988)) and taking logs after adding a small positive value of 0.01 to account for zero values, which yields qualitatively similar results. It reassures that the results are not sensitive to the transformation in particular.

[27] Conditional on working, however, there is no significant effect of the intervention on the intensive margin (workdays or work hours) for wives.

In the non-network treatment group it went up by 1.5 days (6.76%) while in the network group the magnitude was higher (but not significantly different) at 1.901 workdays (8.36%). We find no overall treatment effect on work hours of husbands (Panel B, column (2)) but there was a significant ($p<0.10$) difference across the two treatment arms (Panel B, column (4)). The hours worked per day by husbands in the network treatment arm went up by 0.66 (8.11%) with no effect in T1.

2.4.2 Occupational choice and Earnings

We also examine the impact of the intervention on the type of work (self-employed, salaried, or casual labor) in order to test for occupational shifts in Table 2.7. We find that, while wives experienced no overall treatment impact on their work status as reported in Table 2.5, their self-employment in the network treatment group increased by 4.5 pp (column (3) of Table 2.7). This appears to be accompanied by an insignificant reduction in their engagement in causal labor (column (11), $p>0.10$), indicating a substitution away from precarious work for wives in the network treatment group. We find a similar movement away from casual labor for the non-network treatment group ($p<0.10$), however, a shift to self-employment is absent (column (3), coefficient on T1). This may be a key factor driving the reduction in the work days and work hours of the non-network group, as reported in Table 2.6. There is no significant impact in terms of salaried jobs for women (columns (5) and (7)) in either treatment arm. Husbands too appear to be substituting away from casual work (column (12)), but without a significant increase in self-employment (column (4)).

Next, we examine whether the observed impact on labor force participation and occupational change affected monthly (individual) earnings, as reported in Table 2.8.[28] The overall treatment effect is muted for wives (column (1)), yet hides significant heterogeneity by treatment type. In particular, we find that the non-network treatment wives experienced a contraction in their earnings (imprecisely estimated) relative to the control group (column (3), $p<0.10$), consistent with their withdrawal from casual labor discussed earlier. In contrast, their network treatment counterparts were successful in avoiding such contraction to their earnings (coefficient is significantly different from the non-network coefficient, $p=0.01$). For husbands, the intervention has a large and positive significant impact on average monthly earnings, driven by the network

[28] We add a positive value of 0.01 before the log transformation to account for zero values of earnings. Alternatively, we also use an IHS transformation of monthly earnings and add a positive value of 1 to reported earnings before the log transformation. Results are qualitatively similar and thereby not sensitive to the log transformation.

treatment group whose earnings more than doubled relative to the control group (column (4) of Table 2.8).

In order to shed more light on the nature of the additional earnings of husbands, we also examine in Appendix Table 2A.9 the treatment effects on whether the remuneration for work is in the form of *Salary* (columns (1)-(4)), *Piece-rate* (columns (5)-(8)) and *Daily wage* (columns (9)-(12)). We find that the intervention results in husbands shifting to relatively more secure salaried (column(2)) and away from vulnerable piece-rate (column(6)) and daily wage (column(11)) payment arrangements. While the magnitude of change is similar between the two treatment arms for piece-rate (p=0.86) and daily wage (p=0.66) payments, it is significantly higher for the network treatment husbands relative to the non-network treatment husbands for salaried payments (p=0.09). This provides further confirmation for our earlier findings on occupational shifts for husbands, and the role of network treatment in driving these changes. Consistent with the overall insignificant impact on wives' earnings discussed earlier, the effect on wives' type of earnings also remains muted.

We also instrument for registration on the portal with random assignment to treatment (either T1 or T2) to obtain treatment on treated (TOT) estimates, given the low platform registration rates (about 25% amongst main respondents and 35% amongst treated peers).[29] Our findings are similar – we find an insignificant impact on registered wives' work outcomes with a larger estimate on the intensive margin of work ($\sim$1.5, $p<0.05$) and monthly earnings (=3.3, $p<0.05$) of registered husbands. The impact on the work status of registered husbands (wives) is positive (negative) and close to the ITT effect of T2 at 4.2 pp but imprecisely estimated ($p>0.10$) as in Table 2.5 above.

To summarize, we find that husbands' probability of working, the intensity of work, and earnings in the network treatment group are higher relative to the control group, with no significant gains for the non-network group 14 months after the intervention. In case of wives, while their labor market participation or earnings did not improve overall, we find an increase in the proportion of self-employed married women in the network treatment group.[30] In contrast, we observe a marginal decline in women's work intensity (and hence, earnings) in the non-network treatment group, driven by a reduction in casual work. This may be attributed to their increased awareness and anticipation of improved work opportunities coming through the job portal, that lowered their inclination to take up precarious work. This is consistent with Kelley et al. (2022)

[29] We use the same set of control variables and cluster standard errors at the PS level as in the main specification.
[30] We continue to find similar effects if we condition the sample on those who report working at baseline.

who find that voluntary unemployment among vocational trainees rose due to higher expectations following registration on an online job portal in India.

2.4.3 Attrition

As mentioned previously, attrition is negligible in our data (below 5%). Nonetheless, we restrict the sample to a balanced panel of couples who were successfully followed up in all rounds of the survey to check the robustness of our results to selective attrition. This comprises 96% of our original sample. The regression results for the balanced sub-sample in Appendix Table 2A.10 show that our results remain unchanged. We continue to find that the probability of working, the intensity of work (workdays and work hours), and earnings in the network treatment group for husbands is higher relative to the control group. The higher beneficial effect in T2 (network treatment) over T1 holds for both husbands and their wives.

Furthermore, we follow Ghanem et al. (2021) to test for attrition bias in our sample. For this, we test for the differences in mean baseline outcomes across the treatment arms for the non-attriters and the attriters. Appendix Table 2A.11 reports the baseline mean for two main outcome variables: (i) work status (Panel A), and (ii) average monthly earnings (Panel B). Columns (1)-(3) report the mean for the non-attriters while columns (4)-(6) report it for the attriters. In columns (7)-(8), we report the p-values of the test of mean differences between the treatments and control group for the non-attriters, while the corresponding p-values for attriters are in columns (9)-(10). We find that both these baseline outcomes are similar across control and treated non-attriters in both the treatment arms (columns (7)-(8)) as well as treated and control group attriters (columns (9)-(10)). Additionally, there are no significant differences in both these outcome variables amongst all treatment-response subgroups, i.e. between the treatment and control respondents and attriters. Therefore, the difference in mean outcomes at endline identifies the treatment effect on our sample since the identifying assumption of internal validity is satisfied.[31]

[31]We also carried out the standard inverse-probability weighted (IPW) approach. Our results are robust to correction for selection on observed household and individual characteristics as well as multiple hypotheses tests.

2.5 Mechanisms

2.5.1 Role of social networks

What explains the null effect of the network treatment effect on the labor force participation of wives, and the positive and significant effect on the labor market outcomes of their husbands? We argue that the gendered nature of the social networks of wives and husbands in our setting plays a key role. Two stylized facts are relevant here. First, wives' social networks are more family-centric and home-bound, relative to their husbands'. In particular, as reported in Table 3, 96% of the average woman's peer network consists of non co-resident family members or neighbors compared to 56% for her husband. Second, there exists a significant overlap between wives' peers and their husbands' peers - a quarter of an average wife's peers are her male relatives (e.g. brothers-in-law). Together, this implies that men (and husbands) in the network treatment group likely benefited more than women from the diffusion of information about job opportunities from the job portal within the network, while wives' labor market participation remained constrained.

We directly test this network-based explanation for the positive employment effects of husbands using two approaches. First, we examine the effect of network treatment on the labor market outcomes of the wife's male and female peers separately. We pool the sample of all peers of the wife (baseline + intervention) and instrument the peers' treatment status with a dummy variable that equals one if the wife was assigned to the network treatment group (T2) and zero if she was assigned to either the non-network treatment group (T1) or the control group in a 2SLS specification. The results are reported in Table 2.9.[32] We find that being in the network treatment arm (T2) improved the labor market outcomes of only the male peers of the wife and had no impact on the wife's female peers.[33] Male peers' were more likely to work (Panel A, column (1)), work longer hours (columns (2) - (3)) and enjoy higher earnings (column (4)).[34]

Second, we examine whether the husband's employment varies by the overlap with his wife's

[32] We control for the peers' age, education, and occupation code as reported in the first instance they were surveyed, i.e. at baseline and at intervention (for the new peers suggested for treatment who were not initially surveyed at baseline). Since we do not have baseline data for all the peers, we are not able to control for the baseline labor market outcomes or the household characteristics as in our main specification.

[33] Our results continue to hold qualitatively and with much larger magnitudes when we restrict the sample to peers reported at baseline, confirming that the findings are not driven by a systematic difference in network characteristics between baseline and intervention.

[34] Our finding aligns with Beaman et al. (2018), who show that men are more likely to refer other men for job openings despite knowing qualified women due to strong gender homophily, but women do not, in a field experiment they conduct in Malawi.

network. Husbands in the network treatment who shared their social network with wives (at baseline) were indeed more likely to be employed one year after the intervention (Appendix Table 2A.12, columns (2) and (4)). Presence of non-co-residing relatives and neighbors in the wife's social network (at baseline) benefits husband's work status significantly improves the probability that the husband is working at endline. In addition, using self-reported data, we find that conditional (unconditional) on interest in registering on the portal, husbands in the network treatment group were 15 (5.2) pp more likely to receive job offers as shown in Table 2.11, columns (2) and (4). This was not the case for wives (columns (1) and (3)). Moreover, husbands received 0.20 additional job offers in T2 relative to the T1, as shown in column (6).[35]

The husbands who got job offers from the portal are more likely to be employed at endline. Such increased employment of husbands in the network treatment group may be directly achieved through greater sharing of information within the network, as well as indirectly via referrals from peers of the wife. We find that husbands whose wives had a majority of their treated network made up of family members (specifically, female members) are 4.6 pp (p<0.05) more likely to be employed in T2. We expect women with a larger share of family female peers to face greater social restrictions relative to those with more men in the network, thereby they are more likely to pass on employment opportunities to their husbands or male peers. This possibility is further substantiated by a higher likelihood of employment among husbands if the male peers of the wife got a job offer. Note that a job offer can be passed on to husbands only if they are gender-neutral, i.e. can be performed by both men and women. Indeed, we find that 8 of the total 12 job categories were offered to both men and women. These results are available on request.

To test the network-based explanation for the wives' null effects in employment in the network treatment group, we look at heterogeneous treatment effects by the type of relationship with peers in the baseline. We find that a movement from the 25^{th} to the 50^{th} percentile of the proportion of peers composed of non co-residing relatives is associated with a 4.9 pp ($p<0.01$) lower probability of the wife being employed a year later in the network treatment group, with no such heterogeneity for husbands (Appendix Table 2A.13).[36] This indicates that the structure

[35] Note that the platform records only matched or accepted job offers, not all job offers. Hence we collected detailed data on job offers through the survey at endline. However, the portal data also corroborates our findings from the endline survey. Of the 99 job offers recorded on the platform, more than two-thirds of the job offers were received by individuals treated with the network, compared to those treated without a network. Clearly, the job information flow was larger in T2 relative to T1.

[36] This is obtained by dividing the estimated coefficient of 19.4 pp (column (1) of Appendix Table 2A.13) by the change in the proportion of peers composed of non co-residing relatives as we move from the 25^{th} percentile (=0.5) to the 75^{th} percentile (=0.75).

of the wives' social network constrained their labor market outcomes either due to fewer weak ties (required for job information and referrals) or due to conformation to gender norms, or both. We turn to the role of the latter in the next section.

2.5.2 Role of social norms

What explains the positive effect of the network treatment on wives' self-employment? We find that the wives' increased self-employment in the network treatment group is attributable to an increase in the probability that they were self-employed in their own business manufacturing activity (Appendix Table 2A.14) - primarily home-based work, such as tailoring. Recall that at baseline, among the wives who reported working, the proportion self-employed was the largest. In addition, we observed a high preference (80%) among our couples for home-based work for women and male breadwinner norm. These self-reported preferences are validated by the platform registration data which show that, on average, registered women were willing to travel only half the distance of the male job seekers and preferred jobs that were home-based. Thus our results indicate that in the network treatment group, while husbands took advantage of greater access to job information via the portal, wives conformed to the gender norm of women's role being primarily of a homemaker and working (if at all) from home.

We also find that the treatment effect for wives in the network treatment group is driven by those women whose treated female peers also took up self-employment (column (2) in Appendix Table 2A.15). This suggests that network treatment may have initiated discussions within couples around increased employment opportunities for women. Wives backed by their female peers could now bargain with husbands to jointly start their own manufacturing business that is consistent with underlying gender norms. A similar effect was not observed in the non-network treatment as wives might not have been able to initiate these discussions without support from their network.

Our findings on gender attitudes and norms also show that the perception of treated husbands regarding mothers' childcare responsibilities was similar to the control group (columns (12) and (16) of Appendix Table 2A.16). Further, they showed no increased interest in sharing the domestic chores if the wife worked (see column (16) of Appendix Table 2A.17). These results indicate that while the treatment may have helped in smoothing some of the job search constraints faced by women, it is not sufficient to overcome the burden of domestic work and the resulting mobility constraints faced by them. This mechanism is also validated by the reported reasons why wives didn't take up jobs offered through the portal - family responsibilities and job location.[37]

2.5.3 Alternative explanations

In this section we attempt to rule out other possible explanations for our findings. First, are women less likely to take up new digital technology resulting in the gender-differentiated treatment effects? As Table 2.10 shows, both wives and husbands had higher rates of registration on the platform, conditional on interest, in the network treatment group relative to the non-treatment group (columns (5) and (6)). However, there were no significant gender differences in the take-up of the technology in terms of registration on the platform.[38]

Second, it may be argued that there exists insufficient demand for women's labor, especially if there were systematic gender differences in the recovery of the labor market during the post-pandemic period, which might explain the null effect on women's employment. In other words, women's employment did not increase because there were just no jobs for women. However, the last two rows in Table 2.11 indicate that the (unconditional) job offer rate for wives was similar (if not marginally higher) to that of their husbands (9% compared to 7%) in the placebo group, i.e. the non-network group. Hence, it does not appear to be the case that there was insufficient demand for women's work. Second, looking at the broader time trends of female labor force participation in Delhi and urban India post-pandemic, we find that female employment rates had already begun to recover from losses during the pandemic around the time of our endline in 2021, indicating the potential of digital job search platforms in further boosting demand for women's labor at this time (see Appendix Figure 2A.1).

Third, could the increase in employment rates of husbands in the network treatment group (T2) be driven by a response to job losses during the pandemic? We find no differential employment outcomes for husbands in T2, either by job loss during the pandemic or work status right after the pandemic-induced lockdown at Endline 1 (results available on request). Thus, husbands in T2 who lost their jobs during the pandemic or were not employed up to 6 months after (at Endline 1) show a similar impact of the intervention as husbands who did not lose their jobs during the pandemic or found work.

[37] Child-care and home-production responsibilities, and job being located too far are recurring reasons reported by wives for not registering on the job matching platform.

[38] Furthermore, we do not find any heterogeneity in our results by mobile phone ownership or usage of the respondent.

Fourth, could the observed increase in wives' self-employment in the network treatment group be driven by an income effect or supply-side factors, e.g. increased ability to invest in a home-based venture (viz. purchasing a sewing machine) due to the observed increase in their husband's earnings? We find that the higher participation in self-employment is driven by wives whose husbands were working at baseline but is not positively impacted by gains in husbands' work status or earnings between baseline and endline. This rules out the possible income effect from intervention driving the observed increase in the wife's self-employment.

Fifth, it is possible that network-mediated self-employment opportunities, e.g. changes in labor demand that wives in the network treatment group took advantage of through their network, could be driving the estimated effect. For instance, anecdotal evidence suggests that many manufacturing units switched to stitching masks and PPE kits, primarily by women and possibly outsourced from factories close to women's homes, during the pandemic. Hence, we check for any heterogeneity in treatment effects by the average minimum distance between the polling station and the closest factory (the average minimum distance was 1.4 kms, while the average maximum distance was 3.9 kms). We don't find any difference in treatment effects here, suggesting that network-mediated access to demand for women's labor does not drive the results.

Finally, we do not find evidence of differential impacts of the two treatments on gender norms driving our results. We report the estimated effect of treatment (using our main specification) on indexes of attitudes towards gender roles and women's outside work in Table 2.12.[39] Treatment reduces the index of regressive gender attitudes by almost 0.2 SD for wives and husbands (columns (1) and (2)), compared to the control group. This is not statistically different between treatment groups for both sexes (columns (3) and (4)). While we do not find a strengthening of the progressive attitudes towards women working outside the home, wives in T1 exhibit a more positive attitude (column (5)) but this effect does not differ across the two treatments (column (7)). Moreover, there is a null effect of treatment on the attitudes of husbands toward women's outside work. Clearly, access to technology has the potential to increase the perceived returns to wives' work by weakening regressive gender norms. But being treated with the network has no differential effect on these attitudes, strengthening our proposed channel of a greater flow of job information in the network treatment, that men took advantage of in T2, relative to T1.

[39] See notes to Table 2.12 for details on the construction of the indices. For the disaggregated impact of treatment on gender attitudes by each component of the indexes see Appendix Tables 2A.16 and 2A.17.

2.6 Conclusion

In this study, we implement a cluster RCT in urban India that offers a new job search technology to married couples or offers the technology to the couple along with harnessing the network of the wife by offering the treatment to two of her friends as well. Our results indicate significant positive effects on the labor market participation, work intensity, and earnings of husbands in the network treatment arm compared to the only husband-wife pair treatment, relative to the control group. However, wives' overall labor force participation does not change, although their labor market outcomes are significantly better in the network treatment, they are more likely to report being self-employed when treated with their peers. Although the implications of our findings for women's overall welfare is unclear, existing literature suggests that increased earnings from work outside the home raises women's intra-household bargaining power (e.g. Anderson and Eswaran (2009)). Given our results, we do not find any improvement in the say wives' have in intra-household decision-making in either treatment arm.

These findings highlight the role of gendered social networks and social norms in producing gender-differentiated effects of new technology on labor market outcomes. While social networks play a role in the adoption of new technology, their gendered structure may benefit men and also lead to conformation to prevalent social norms.

2.7 Figures and Tables

Figure 2.1: Sampled districts, and polling stations by treatment status

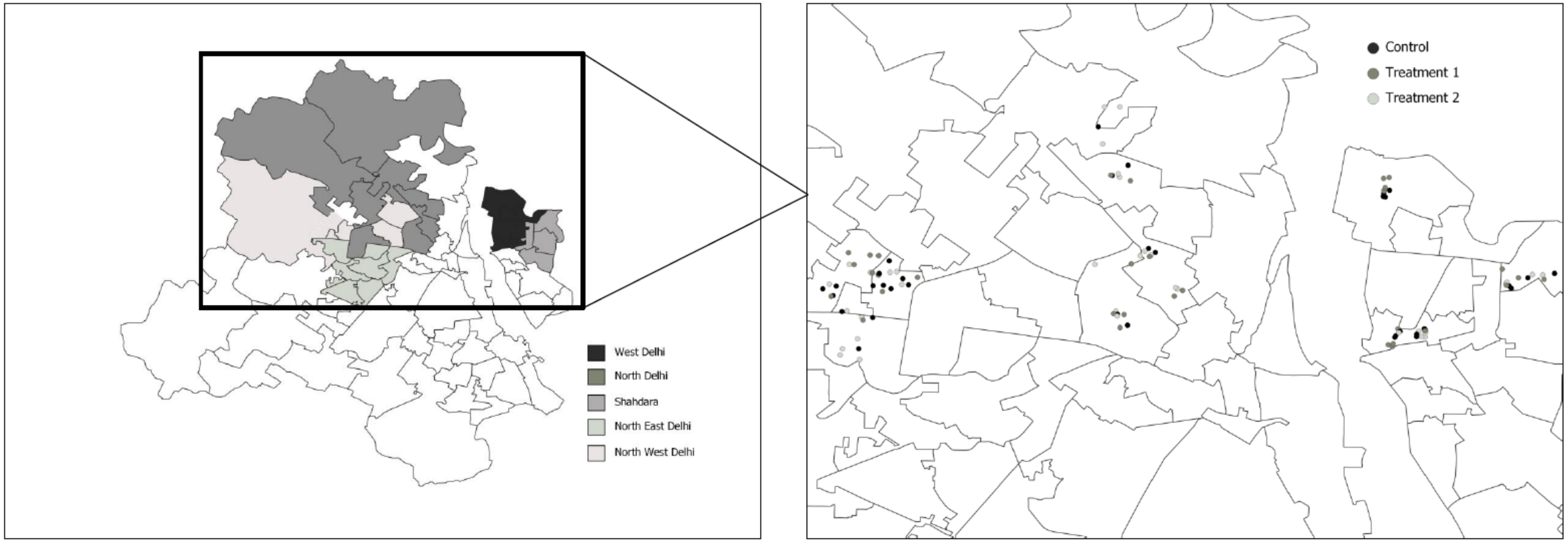


Table 2.1: Timeline of study

Date	**Round**	**Unit**	**Full Sample**	**Matched Sample**
May-July 2019	Baseline	Household	1613	1514
		Individual	3127	3028
		Peers in Network	3468	3468
Nov 2019–Jan 2020	Intervention	Household	1549	1383
		Individual	2972	2878
		Peers in Network	893 (treated)	881
Apr-Aug 2020	Nation-wide Lockdown Due to Covid-19 Pandemic			
Aug-Nov 2020	First Endline	Household,	1588	1449
		Individual	3069	2976
		Peers in Network	3583 (baseline+treated)	3575
Apr-June 2021	Second Endline	Household,	1555	1422
		Individual	2981	2891
		Peers in Network	3522 (baseline+treated)	3511

Table 2.2: Summary statistics (at baseline)

Variable	N	Mean	S.D.	Definition
Panel A: Household Characteristics				
Household Size	1514	5.29	1.84	number of household members
Joint Family	1514	0.19	0.39	=1 if more than one couple present in the household, 0 otherwise
Young Children	1514	0.57	0.70	=1 if the couple has children below 5 years of age, 0 otherwise
Hindu	1514	0.82	0.38	=1 if household reports Hindu religion, 0 otherwise
SC/ST	1510	0.44	0.50	=1 if household belongs to scheduled Caste or Tribe, 0 otherwise
Asset Index	1471	0.00	1.00	PCA of assets
Native	1514	0.36	0.48	=1 if household native of Delhi, 0 otherwise
Years of stay	1512	28.76	14.08	number of years the household has stayed in current location
Panel B: Individual Characteristics				
Age	3028	32.71	6.52	years
Education	3025	0.62	0.48	=1 if above primary level of education, 0 otherwise
Phone usage	3028	0.94	0.24	=1 if use mobile phone, 0 otherwise
Working	3028	0.60	0.49	=1 if working, 0 otherwise
Casual labor	3028	0.16	0.37	=1 if working for wages in factories, construction, domestic help or other casual activities, 0 otherwise
Self-employed	3028	0.21	0.41	=1 if self-employed in retail, own business manufacturing or other self-employment activities, 0 otherwise
Salaried	3028	0.22	0.41	=1 if working as salaried employee in government or non-government organisations, 0 otherwise
Unemployed	3028	0.03	0.16	=1 if not working but looking for work, 0 otherwise
Not in labor force	3028	0.38	0.48	=1 if not working and not looking for work, 0 otherwise
Earnings	3028	6027.65	13207.69	Monthly income (in INR)
Earnings (Conditional)	1691	10793.45	16154.85	Monthly income conditional on being employed
Panel C: Network Characteristics				
Age	3466	36.23	11.39	in years
Female	3468	0.38	0.48	=1 for females, 0 otherwise
Education	3462	0.66	0.48	=1 if above primary level of education, 0 otherwise
Working	3468	0.64	0.48	=1 if working, 0 otherwise
Unemployed	3468	0.06	0.23	=1 if not working but looking for work, 0 otherwise
Not in labor force	3468	0.31	0.46	=1 if not working and not looking for work, 0 otherwise

Note: The *Asset Index* is constructed using the principal components analysis (PCA) on the households' ownership of different assets (flat, box TV, LCD TV, fridge, clock, stove, cycle, bike, car fan, cooler, AC, computer, mobile, sewing machine, agricultural land, rented land and farm animals).

Table 2.3: Work status and social networks, by gender (at baseline)

	Wife	Husband	Wife-Husband
	Panel A: Labor Force Participation		
Working	0.24	0.96	-0.72***
	(0.42)	(0.20)	
Casual labor	0.07	0.25	-0.18***
	(0.26)	(0.44)	
Self-employed	0.11	0.30	-0.19***
	(0.32)	(0.46)	
Salaried	0.04	0.40	-0.35***
	(0.21)	(0.49)	
Unemployed	0.02	0.04	-0.02***
	(0.13)	(0.19)	
Not in labor force	0.75	0.01	0.74***
	(0.13)	(0.19)	
Monthly earnings (INR)	908.48	11146.82	-10238***
	(75.29)	(436.13)	
	Panel B: Social Network (by relationship and gender)		
Non co-resident relative	0.75	0.39	0.35***
	(0.30)	(0.37)	
Friend	0.04	0.37	-0.33***
	(0.12)	(0.37)	
Neighbor	0.21	0.17	0.04***
	(0.29)	(0.27)	
Co-worker	0.00	0.07	-0.06***
	(0.04)	(0.18)	
Female	72.06	12.38	59.68***
	(0.25)	(0.21)	
N	1514	1514	

Note: In Panel A, we report the mean labor force participation of wives and husbands at baseline. An individual is either working, unemployed (and looking for work) or not in labor force (not working and not looking for work). Working status is classified into three categories - (1) Casual labor, (2) Self-employment and (3) Salaried Work. In Panel B, the social network of an individual is classified on the basis of the relationship with the member in the network at baseline. These can be relatives who are not co-residing with the respondent, friends, neighbors or co-workers. In each Panel, the last column reports the difference in the mean value of wife and husband (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.4: Attitudes and preferences towards women's work, by gender (at baseline)

	Wife (1)	Husband (2)	Wife - Husband (3)
Panel A: Attitude towards gender roles			
Woman should take care of home	0.8	0.88	-0.078***
	(0.4)	(0.33)	
Woman should support husband's career	0.86	0.73	0.13***
	(0.34)	(0.44)	
If mother works children suffer	0.88	0.88	0
	(0.33)	(0.33)	
If mother works poor relationship with children	0.36	0.3	0.06***
	(0.48)	(0.46)	
N	1513	1510	
Panel B: Attitude towards women's outside work			
Woman can travel outside locality	0.88	0.88	-0.01
	(0.33)	(0.33)	
Woman can work outside home	0.91	0.84	0.06***
	(0.29)	(0.36)	
Woman can work even if husband provides	0.6	0.33	0.27***
	(0.49)	(0.47)	
If woman works husband shares domestic duties	0.95	0.97	-0.025***
	(0.22)	(0.16)	
N	1513	1506	
Panel C: Job preferences for women			
Salaried	0.67	0.78	-0.10***
	(0.47)	(0.42)	
Casual	0.08	0.03	0.05***
	(0.27)	(0.18)	
Domestic help	0.02	0.01	0.01***
	(0.15)	(0.09)	
Home-based	0.81	0.78	0.03**
	(0.39)	(0.41)	
Should not work	0.02	0.03	-0.1**
	(0.13)	(0.17)	
N	1514	1514	

Note: In Panels A and B, each row is an indicator variable that takes value one if an individual agrees with a statement, and zero otherwise. In Panel A, the questions corresponding to each row were: (1) It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family; (2) It is more important for a wife to help her husband's career than to have one herself; (3) When a mother works for pay, the children suffer; (4) A working mother cannot establish just as warm and secure a relationship with her children as a mother who does not work. In Panel B, the corresponding questions were: (1) In your opinion, is it acceptable for an adult woman to travel outside the locality if she wants to?; (2) In your opinion, should an adult woman work outside of home if she wants to?; (3) Do you approve of a married woman earning money if she has a husband capable of supporting her?; (4) In your opinion, if the wife is working outside the home, should the husband help her with household/care duties? Panel C lists the type of jobs considered suitable for themselves by wives (column (1)) and by husbands for their wives (column (2)). Each row of the table indicates a type of job which takes value one if an individual reported it to be suitable for herself/wife and zero otherwise. $Salaried$ indicates job in govt or private establishment (e.g. office, school, hospital), $Casual$ indicates factory-based or construction work, Domestic help is domestic work, $Home - based$ is work from home and Not work represents preference for not working at all. The last column (column (3)) reports the differential in wife's and husband's attitudes and preferences (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.5: Impact of treatment on work status ($>$ 1 year after intervention)

	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)
Treatment	-0.013	0.012		
	(0.025)	(0.018)		
T1 (without network)			-0.044	-0.018
			(0.027)	(0.020)
T2 (with network)			0.019	0.044**
			(0.029)	(0.020)
Baseline Y	0.938***	0.193	0.919***	0.191
	(0.035)	(0.173)	(0.041)	(0.178)
p-value [T1=T2]			[0.02]	[0]
Observations	1,377	1,377	1,377	1,377
R-squared	0.177	0.046	0.181	0.053
Mean Y	0.23	0.94	0.23	0.94

Note: The dependent variable is an indicator variable that takes value one if an individual is working in reference period and zero otherwise. Columns (1)-(2) report the combined treatment effect using equation (3B.1) while Columns (3)-(4) report it for equation (2.2), by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.6: Impact of treatment on work status on the intensive margin (> 1 year after intervention)

	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)
Panel A: Number of days worked in a month				
Treatment	-0.484	1.715**		
	(0.545)	(0.771)		
T1 (without network)			-1.228**	1.539*
			(0.591)	(0.820)
T2 (with network)			0.286	1.901**
			(0.639)	(0.830)
Baseline Y	0.182***	0.080*	0.185***	0.080*
	(0.067)	(0.047)	(0.067)	(0.047)
p-value [T1=T2]			[0.01]	[0.54]
Observations	1,377	1,377	1,377	1,377
R-squared	0.173	0.048	0.177	0.048
Mean Y	5	22.75	5	22.75
Panel B: Number of hours worked in a day				
Treatment	-0.191	0.435		
	(0.156)	(0.326)		
T1 (without network)			-0.367**	0.221
			(0.176)	(0.345)
T2 (with network)			-0.009	0.661*
			(0.180)	(0.353)
Baseline Y	0.283***	0.186***	0.284***	0.186***
	(0.071)	(0.034)	(0.071)	(0.034)
p-value [T1=T2]			[0.04]	[0.08]
Observations	1,377	1,362	1,377	1,362
R-squared	0.193	0.058	0.196	0.061
Mean Y	1.05	8.15	1.05	8.15

Note: The dependent variable in Panel A (B) is the average number of days worked in a month (the number of hours worked in a day) in the reference period. Days worked in a month were calculated by multiplying the number of days worked in a week by four. In Panel B, we drop the outliers where the number of hours reported were above 14 per day. Columns (1)-(2) report the combined treatment effect using equation (3B.1) while Columns (3)-(4) report it for equation (2.2), by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). In Panel A and B, 'Mean Y' denotes the mean value of workdays and work hours (without IHS transformation), respectively, for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.7: Impact of treatment on type of work (> 1 year after intervention)

Employment Type	Self-employed				Salaried				Casual labor			
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.015	0.036			-0.001	0.027			-0.030*	-0.042		
	(0.016)	(0.025)			(0.009)	(0.026)			(0.017)	(0.032)		
T1 (without network)			-0.013	0.042			0.001	0.016			-0.034*	-0.067*
			(0.014)	(0.026)			(0.011)	(0.029)			(0.020)	(0.036)
T2 (with network)			0.045**	0.030			-0.002	0.039			-0.025	-0.016
			(0.022)	(0.031)			(0.011)	(0.031)			(0.017)	(0.039)
Baseline Y	0.158***	0.417***	0.157***	0.416***	0.340***	0.290***	0.340***	0.291***	0.332***	0.228***	0.332***	0.226***
	(0.041)	(0.032)	(0.041)	(0.032)	(0.071)	(0.035)	(0.071)	(0.035)	(0.056)	(0.064)	(0.057)	(0.064)
p-value [T1=T2]			[0]	[0.68]			[0.81]	[0.46]			[0.6]	[0.18]
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377
R-squared	0.073	0.225	0.082	0.226	0.182	0.148	0.182	0.149	0.128	0.116	0.128	0.118
Mean Y	0.12	0.32	0.12	0.32	0.05	0.39	0.05	0.39	0.06	0.23	0.06	0.23

Note: The dependent variable is an indicator variable for type of work. In Columns(1)-(4), it takes value one if an individual is self-employed and zero otherwise. Similarly, Columns (5)-(8) and Columns(9)-(12) are indicator variables for salaried and casual labor, respectively. Columns (1)-(2), (5)-(6) and (9)-(10) report the combined treatment effect using equation (3B.1) while Columns (3)-(4), (7)-(8) and (11)-(12) report the treatment-wise effect for equation (2.2), by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.8: Impact of treatment on monthly earnings (> 1 year after intervention)

	Wife (1)	Husband (2)	Wife (3)	Husband (4)
Treatment	-0.211	0.924**		
	(0.299)	(0.442)		
T1 (without network)			-0.605*	0.668
			(0.320)	(0.463)
T2 (with network)			0.196	1.195**
			(0.349)	(0.467)
ln(Baseline level)	0.232***	0.082*	0.238***	0.083*
	(0.082)	(0.045)	(0.082)	(0.045)
p-value [T1=T2]			[0.01]	[0.08]
Observations	1,377	1,377	1,377	1,377
R-squared	0.178	0.045	0.183	0.047
Mean Y	889.07	11515.43	889.07	11515.43

Note: The dependent variable is a log transformation of the monthly earnings. Columns (1)-(2) report the combined treatment effect using equation (3B.1) while Columns (3)-(4) report it for equation (2.2), by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of monthly earnings (without log transformation) for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 2.9: Impact of treatment on employment outcomes of wife's network (2SLS) (> 1 year after intervention)

	Extensive Margin	Intensive Margin (ln)		
	Working	Days (per week)	Hours (per day)	Income (Monthly)
	(1)	(2)	(3)	(4)
	Panel A: Male peers			
Treatment	0.118***	1.236***	1.209***	2.983***
	(0.044)	(0.412)	(0.381)	(0.946)
Observations	394	394	394	394
R-squared	0.160	0.140	0.144	0.129
Mean Y	0.79	6.8	4.43	8843.30
	Panel B: Female peers			
Treatment	-0.025	-0.275	-0.213	-0.383
	(0.030)	(0.236)	(0.232)	(0.483)
Observations	1,428	1,428	1,428	1,428
R-squared	0.139	0.152	0.148	0.149
Mean Y	0.19	1.34	1.04	2640.48

Note: The sample consists of all (baseline + intervention) peers of the wife in T1, T2 and the control group. 'Treatment' is a dummy variable that equals one if the wife's peer was offered platform registration and zero otherwise. We use 2SLS estimation model and instrument the peers' treatment status with a dummy for whether the wife was randomly assigned to T2 or not. The dependent variable in column (1) is an indicator variable that equals one if the peer is working in the reference period, and 0 otherwise. Columns (2)-(4) are the IHS transformations of the workdays (per week), hours (per day), and monthly earnings. ANOVA specification is used in this analysis as intensive margin data of peers is not reported at the baseline. 'Mean Y' denotes the mean value for the peers of wives in the benchmark group (control + T1) at Endline 1 of the dependent variable in Column (1) and mean value without IHS transformation for the dependent variables in Columns (2)-(4). Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.10: Impact of network on interest in and registration on job matching platform

	Interested		Registered (Unconditional)		Registered (Conditional on interest)	
	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)
T2 (with network)	-0.021	-0.090**	0.034	0.033	0.079*	0.126***
	(0.049)	(0.040)	(0.033)	(0.026)	(0.046)	(0.038)
Difference (Wife-Husband)	0.069**		0.001		-0.048	
	(0.034)		(0.035)		(0.052)	
Observations	921	922	921	922	562	621
R-squared	0.048	0.042	0.064	0.041	0.084	0.079
Mean T2	0.66	0.67	0.25	0.29	0.42	0.47
Mean T1	0.66	0.75	0.22	0.26	0.35	0.36

Note: The sample is restricted to the treatment 1 (T1) and treatment 2 (T2) groups. The dependent variables are indicator variables that take a value of one if an individual reports being interested in registering for the portal (Columns (1)-(2)), registers on the portal (Column (3)-(4)) unconditional on being interested to register, and registers on the portal conditional on being interested in registering (Column (5)-(6)). The first row reports the impact of T2 relative to the benchmark category of T1. The second row (*Difference*) reports difference in the estimated coefficients of each dependent variable for the wife and the husband. 'Mean T2 (Mean T1)' reports the mean of the dependent variable for T2 (T1) group. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.11: Impact of treatment on job-offers from matching platform (self-reported)

	Job offer (Unconditional)		Job offer		Job offers (Count)	
	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)
T2 (with network)	0.001	0.052**	0.022	0.150***	0.080	0.202***
	(0.020)	(0.021)	(0.041)	(0.045)	(0.056)	(0.069)
Difference (Wife-Husband)	-0.051*		-0.128**		-0.122	
	(0.027)		(0.059)		(0.085)	
Observations	886	887	362	348	362	348
R-squared	0.012	0.018	0.041	0.071	0.038	0.065
Mean T2	0.09	0.11	0.23	0.3	0.3	0.37
Mean T1	0.09	0.07	0.21	0.17	0.23	0.19

Note: The sample is restricted to the treatment 1 (T1) and treatment 2 (T2) groups. The dependent variables in columns (1) - (2) are indicator variables that equal one if an individual reports receiving a job offer from the portal, and 0 otherwise. In columns (3)-(4)), the indicator of job offer is conditional on registration on the portal. Columns (5)-(6) report the number of job offers received during the reference period, conditional on registration. The first row reports the impact of T2 relative to the benchmark category of T1. The second row (*Difference*) reports difference in the estimated coefficients of each dependent variable for the wife and the husband. 'Mean T2 (Mean T1)' reports the mean of the dependent variable for T2 (T1) group. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2.12: Impact of treatment on gender attitudes (> 1 year after intervention)

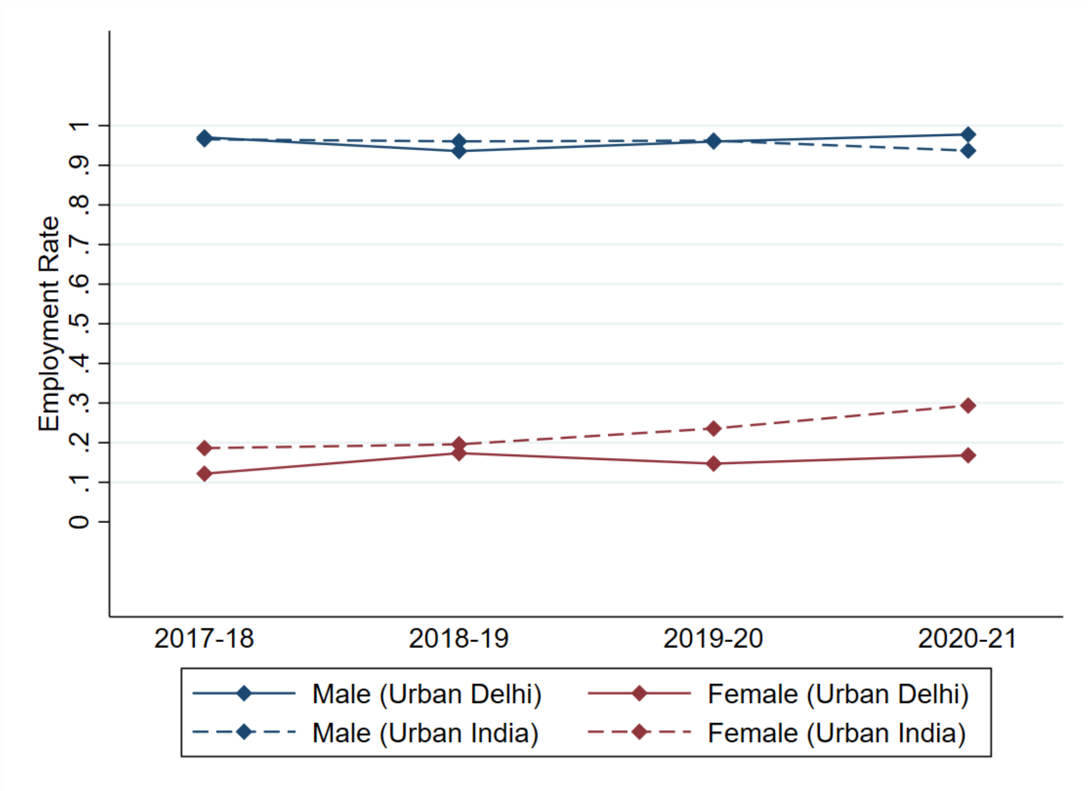
	Index of attitude towards gender roles				Index of attitude towards women's outside work			
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.188***	-0.196***			0.081*	-0.047		
	(0.069)	(0.052)			(0.046)	(0.042)		
T1 (without network)			-0.227***	-0.224***			0.109**	-0.045
			(0.083)	(0.056)			(0.050)	(0.048)
T2 (with network)			-0.148*	-0.166**			0.053	-0.048
			(0.085)	(0.078)			(0.052)	(0.051)
Baseline Y	0.053	0.045	0.050	0.044	0.087**	0.155***	0.088**	0.155***
	(0.039)	(0.037)	(0.039)	(0.037)	(0.035)	(0.032)	(0.035)	(0.032)
p-value [T1=T2]			[0.41]	[0.5]			[0.19]	[0.95]
Observations	1,375	1,372	1,375	1,372	1,375	1,370	1,375	1,370
R-squared	0.043	0.033	0.045	0.034	0.050	0.059	0.051	0.059
Mean Y	0.04	-0.05	0.04	-0.05	0.09	-0.08	0.09	-0.08

Note: The dependent variables are Attitude Indices created by taking an equal weighted average of the standardised Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the responses to questions on gender attitudes. In columns(1)-(4), we have Index of attitudes towards gender roles that is constructed using responses to - (1) It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family, (2) It is more important for a wife to help her husband's career than to have one herself, (3) When a mother works for pay, the children suffer, (4) A working mother cannot establish just as warm and secure a relationship with her children as a mother who does not work. And in columns (5)-(8), the Index of attitudes towards women's outside work is weighted average of the responses to the following questions - (1) In your opinion, is it acceptable for an adult woman to travel outside the locality if she wants to?, (2) In your opinion, should an adult woman work outside of home if she wants to?, (3) Do you approve of a married woman earning money if she has a husband capable of supporting her? and (4) In your opinion, if the wife is working outside the home, should the husband help her with household/care duties? Columns (1)-(2) and (5)-(6) report the combined treatment effect using equation (3B.1) while Columns (3)-(4) and (7)-(8) report the treatment-wise effect, by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

2.A Appendices

2.A.A Additional Figures and Tables

Figure 2A.1: Employment trends by gender



Source: Periodic Labour Force Survey (PLFS) of India, 2017-18, 2018-19, 2019-20 and 2020-21.
Note: Employment rate is the proportion of married individuals in the 18-45 age group in urban India (or urban Delhi) who spent a majority of their time during the preceding 365 days from the date of survey in any economic activity as self-employed worker, wage/salaried worker or casual wage laborer.

Table 2A.1: Worker registrations on HNM job portal, by occupation and gender

Job Profiles	Worker registrations			Featured for job opening			Called for job by employer	
	Workers	Prop Female	Distance	Workers	Prop Female	Distance	Workers	Prop Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overall	**26103**	**0.69**	**4.07**	**5299**	**0.86**	**2.13**	**3603**	**0.87**
Babysitter	607	1.00	3.04	421	1.00	2.35	285	1.00
Beautician	270	0.91	4.92	7	1.00	2.68	4	1.00
Cook	1256	0.93	3.17	1939	0.89	2.04	1329	0.89
Driver	523	0.02	6.79	189	0.01	3.72	125	0.00
Electronic Technician	209	0.03	10.07					
Maid/domestic helper	8095	0.89	3.33	2519	0.94	1.97	1720	0.95
Medical Helper	208	0.67	5.19					
Office Helper	6863	0.45	4.58	144	0.12	2.36	88	0.07
Salesperson	2087	0.53	4.88	19	0.00	4.06	9	0.00
Other	285	0.10	6.11	12	0.00	7.86	7	0.00
Other Helper	5390	0.80	3.76	45	0.29	3.32	32	0.19
Other Technician	310	0.02	5.70	4	0.00	3.77	4	0.00

Note: We summarise the job profiles workers registered for on the portal and the job profiles for which they were featured and called for by the employers on the portal in the financial year 2019-20. Columns (1)-(3) list the preferences of registered workers - the total number of job profiles workers have registered (column (1)), the proportion of women in the total works registered (column (2)), and the distance they are willing to travel (in Km) (column (3)). Columns (4)-(6) record the number of workers who were featured for various jobs (column (4)), the proportion of women featured for these jobs (column (5)), and the distance of the workers from employers (column (6)). Lastly, columns (7)-(8) list the number of workers who were called (column (7)) for the featured jobs and the proportion of women called for these jobs (column (8)). *Other* includes job profiles of Raj Mistry, Marble Mistry, Machine Operator, Bartender, Supervisor *Other Helper* includes Labour, Salon Helper, Stitching Helper, Security Guard and *Other Technician* comprises Construction Painter, Electronic Technician, Electrical Technician, Construction Carpenter, Construction Plumber.

Table 2A.2: Summary of registration rates on the online job portal

	Main respondents (all treatments)							Wife's Peers (in T2)		
	All	Wife			Husband			All	Female	Male
Variable		T1 & T2	T1	T2	T1 & T2	T1	T2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Interested	67.06	64.58	64.97	64.19	69.54	73.39	65.59	69.93	69.38	72.12
	(2016)	(1008)	(511)	(497)	(1008)	(511)	(497)	(828)	(663)	(165)
Registered	36.69	34.87	32.23	37.62	38.37	34.93	42.33	46.63	46.09	48.74
(Conditional)	(1352)	(651)	(332)	(319)	(701)	(375)	(326)	(579)	(460)	(119)
Registered	25.05	23.02	21.53	24.55	27.08	25.83	28.37	32.85	32.28	35.15
(Unconditional)	(2016)	(1008)	(511)	(497)	(1008)	(511)	(497)	(828)	(663)	(165)

Note: The matched husband and wife pairs in the two treatment arms and peers of wives in the network treatment arm (T2) were offered to register on the job portal. The first row reports the *Interest rate* of the respondents to join the portal. The second and third row report the Conditional and Unconditional *Registration rates*, respectively. The former conditions registration on being interested in on-boarding the portal while the latter is unconditional. Columns (1)-(7) list the sign-up rates for the main respondents - overall (column (1)), for the treated wives (column (2)) and their husbands (column (5)). Columns (3)-(4) and columns (6)-(7) report the treatment-wise averages for the treated wives and husbands, respectively. And the columns (8)-(10) report it for the peers of wife in T2 who were offered the same service - overall (column (8)) and by gender of the peer in columns (9) and (10). The number of respondents per category in parentheses.

Table 2A.3: Balance of household characteristics (at baseline)

	Control	**Treatment**		**Difference**		
	C	**T1**	**T2**	**C-T1**	**C-T2**	**T1-T2**
	(N=506)	**(N=511)**	**(N=497)**			
	(1)	(2)	(3)	(4)	(5)	(6)
Household Size	5.308	5.256	5.318	0.052	-0.010	-0.062
	(0.086)	(0.068)	(0.089)	(0.109)	(0.123)	(0.111)
SC/ST	0.405	0.445	0.464	-0.040	-0.059	-0.019
	(0.038)	(0.043)	(0.043)	(0.057)	(0.057)	(0.060)
OBC	0.344	0.313	0.302	0.031	0.041	0.011
	(0.037)	(0.028)	(0.032)	(0.046)	(0.048)	(0.042)
Hindu	0.789	0.869	0.811	-0.080	-0.022	0.058
	(0.048)	(0.038)	(0.041)	(0.061)	(0.063)	(0.055)
Pucca house	0.964	0.959	0.970	0.006	-0.005	-0.011
	(0.014)	(0.013)	(0.015)	(0.019)	(0.020)	(0.019)
Have tapped water	1.263	1.249	1.276	0.014	-0.013	-0.027
	(0.032)	(0.031)	(0.037)	(0.044)	(0.048)	(0.048)
Have ration card	0.638	0.593	0.630	0.045	0.008	-0.037
	(0.026)	(0.032)	(0.022)	(0.041)	(0.034)	(0.039)
Asset Index	0.015	-0.067	0.044	0.082	-0.028	-0.110*
	(0.044)	(0.036)	(0.056)	(0.056)	(0.070)	(0.066)
Years staying in current location	28.433	29.108	28.722	-0.675	-0.289	0.386
	(0.904)	(1.001)	(0.977)	(1.339)	(1.322)	(1.389)
Joint family	0.208	0.182	0.189	0.026	0.018	-0.007
	(0.019)	(0.022)	(0.015)	(0.029)	(0.024)	(0.027)
Number of young children	0.593	0.562	0.565	0.031	0.027	-0.004
	(0.037)	(0.029)	(0.035)	(0.046)	(0.050)	(0.045)
Native of Delhi	0.346	0.372	0.358	-0.026	-0.012	0.014
	(0.032)	(0.043)	(0.040)	(0.053)	(0.051)	(0.058)
p-values for joint significance	-	-	-	[0.386]	[0.991]	[0.169]

Note: The sample here is restricted to matched husband-wife pair data. T1 denotes treatment where only main respondents (husband-wife pair) were offered the job aggregator service, T2 represents treatment in which the main respondents and two of the wife's peers were offered this service and C denotes the control group where no such service was offered. The p-values reported in the last row of the table correspond to F-test of joint significance of household characteristics in determining the treatment status in a linear probability model. Standard errors, clustered at the PS level, are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.4: Balance of individual characteristics (at baseline)

	Wife						Husband					
	Control	Treatment		Difference			Control	Treatment		Difference		
	C	T1	T2	C-T1	C-T2	T1-T2	C	T1	T2	C-T1	C-T2	T1-T2
	(N=506)	(N=511)	(N=497)				(N=506)	(N=511)	(N=497)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age	30.547	30.777	30.934	-0.229	-0.386	-0.157	34.579	34.622	34.833	-0.043	-0.254	-0.211
	(0.306)	(0.284)	(0.290)	(0.415)	(0.418)	(0.403)	(0.347)	(0.332)	(0.301)	(0.477)	(0.456)	(0.445)
Education	0.590	0.551	0.567	0.039	0.023	-0.016	0.673	0.671	0.694	0.002	-0.021	-0.023
	(0.026)	(0.035)	(0.033)	(0.043)	(0.041)	(0.047)	(0.030)	(0.033)	(0.031)	(0.044)	(0.043)	(0.045)
Years married	11.504	11.912	11.871	-0.408	-0.367	0.041	11.504	11.912	11.871	-0.408	-0.367	0.041
	(0.351)	(0.317)	(0.378)	(0.470)	(0.512)	(0.489)	(0.351)	(0.317)	(0.378)	(0.470)	(0.512)	(0.489)
No. of children	2.168	2.211	2.192	-0.043	-0.024	0.020	2.168	2.211	2.192	-0.043	-0.024	0.020
	(0.063)	(0.065)	(0.073)	(0.090)	(0.096)	(0.097)	(0.063)	(0.065)	(0.073)	(0.090)	(0.096)	(0.097)
Mobile usage	0.915	0.894	0.913	0.021	0.002	-0.019	0.962	0.977	0.978	-0.014	-0.015	-0.001
	(0.020)	(0.021)	(0.017)	(0.029)	(0.027)	(0.027)	(0.010)	(0.010)	(0.009)	(0.014)	(0.014)	(0.013)
Skill Trained	0.172	0.186	0.177	-0.014	-0.005	0.009	0.043	0.051	0.046	-0.007	-0.003	0.005
	(0.020)	(0.023)	(0.022)	(0.030)	(0.030)	(0.031)	(0.009)	(0.009)	(0.008)	(0.013)	(0.012)	(0.012)
Number of Peers	3.931	4.297	3.915	-0.367*	0.015	0.382*	3.069	3.139	3.201	-0.070	-0.132	-0.062
	(0.122)	(0.182)	(0.112)	(0.218)	(0.164)	(0.212)	(0.074)	(0.068)	(0.078)	(0.100)	(0.107)	(0.102)
Number of peers with mobile	1.923	1.875	1.944	0.048	-0.021	-0.069	2.077	2.108	2.107	-0.031	-0.030	0.001
	(0.069)	(0.072)	(0.076)	(0.099)	(0.101)	(0.104)	(0.084)	(0.105)	(0.077)	(0.133)	(0.113)	(0.129)
Native	0.395	0.401	0.400	-0.006	-0.006	0.001	0.526	0.566	0.584	-0.040	-0.058	-0.018
	(0.024)	(0.032)	(0.030)	(0.040)	(0.038)	(0.044)	(0.032)	(0.034)	(0.037)	(0.046)	(0.048)	(0.050)
Years in Delhi	19.472	19.573	19.382	-0.101	0.090	0.191	30.423	28.746	30.753	1.677	-0.330	-2.007
	(0.567)	(0.784)	(0.702)	(0.961)	(0.897)	(1.046)	(1.656)	(0.802)	(1.471)	(1.828)	(2.200)	(1.664)
Casual labor	0.063	0.084	0.076	-0.021	-0.013	0.008	0.235	0.239	0.288	-0.004	-0.053	-0.049
	(0.012)	(0.017)	(0.018)	(0.021)	(0.021)	(0.024)	(0.028)	(0.026)	(0.027)	(0.038)	(0.039)	(0.037)
Self-employed	0.123	0.102	0.119	0.021	0.004	-0.017	0.322	0.290	0.294	0.033	0.028	-0.004
	(0.017)	(0.015)	(0.017)	(0.023)	(0.024)	(0.023)	(0.023)	(0.025)	(0.031)	(0.034)	(0.038)	(0.039)
Salaried	0.049	0.041	0.044	0.008	0.005	-0.003	0.379	0.431	0.380	-0.051	-0.001	0.050
	(0.012)	(0.010)	(0.010)	(0.015)	(0.015)	(0.014)	(0.030)	(0.030)	(0.029)	(0.042)	(0.042)	(0.042)
Unemployed	0.008	0.025	0.022	-0.018*	-0.014	0.003	0.047	0.033	0.026	0.014	0.021*	0.007
	(0.004)	(0.009)	(0.008)	(0.010)	(0.009)	(0.012)	(0.009)	(0.010)	(0.008)	(0.013)	(0.012)	(0.012)
Attitude Index	-0.067	-0.052	-0.084	-0.015	0.017	0.032	-0.125	-0.160	-0.128	0.034	0.002	-0.032
	(0.032)	(0.034)	(0.031)	(0.047)	(0.045)	(0.046)	(0.020)	(0.021)	(0.018)	(0.029)	(0.027)	(0.028)
Norm Index	-0.008	-0.010	-0.011	0.002	0.003	0.001	-0.010	-0.009	-0.014	-0.001	0.004	0.005
	(0.031)	(0.031)	(0.029)	(0.043)	(0.042)	(0.042)	(0.025)	(0.031)	(0.038)	(0.040)	(0.045)	(0.049)
Decision making Index	-0.109	-0.134	-0.152	0.025	0.043	0.019	-0.105	-0.076	-0.114	-0.029	0.009	0.038
	(0.022)	(0.023)	(0.019)	(0.031)	(0.029)	(0.029)	(0.026)	(0.028)	(0.027)	(0.038)	(0.037)	(0.038)
p-values for joint significance				[0.812]	[0.774]	[0.917]				[0.519]	[0.502]	[0.769]

Note: The sample here is restricted to matched husband-wife pair data. T1 denotes treatment where only main respondents (husband-wife pair) were offered the job aggregator service, T2 represents treatment in which the main respondents and two of the wife's peers were offered this service and C denotes the control group where no such service was offered. The p-values reported in the last row of the table correspond to F-test of joint significance of individual characteristics in determining the treatment status in a linear probability model. Standard errors, clustered at the PS level, are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.5: Structure of social network by gender of main respondent

	Male Peer Type				Female Peer Type			
	Relative	Friend	Neighbor	Work	Relative	Friend	Neighbor	Work
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Husband (all, at baseline)								
Prop of network	0.38	0.37	0.12	0.05	0.05	0.00	0.02	0.00
	(0.44)	(0.44)	(0.30)	(0.21)	(0.20)	(0.05)	(0.12)	(0.03)
Age (in years)	37.02	33.48	36.76	34.43	41.82	39.00	40.64	36.67
	(11.38)	(9.04)	(10.85)	(10.08)	(12.46)	(16.49)	(11.71)	(18.72)
Working	0.90	0.92	0.85	0.97	0.23	0.20	0.33	1.00
	(0.30)	(0.27)	(0.36)	(0.18)	(0.43)	(0.45)	(0.48)	(0.00)
N	679	682	222	94	90	5	33	3
Panel B: Wife (all, at baseline)								
Prop of network	0.23	0.00	0.05	0.00	0.57	0.02	0.12	0.00
	(0.38)	(0.06)	(0.20)	(0.03)	(0.45)	(0.13)	(0.29)	(0.03)
Age (in years)	35.65	32.60	36.06	32.00	37.67	29.47	36.01	40.00
	(12.06)	(7.44)	(12.65)		(12.42)	(8.64)	(10.12)	(16.97
Working	0.88	1.00	0.88	1.00	0.19	0.36	0.20	1.00
	(0.33)	(0.00)	(0.32)		(0.39)	(0.48)	(0.40)	(0.00)
N	382	5	77	1	935	45	189	2
Panel C: Wife (T2, at intervention)								
Prop of network	0.11	0.03	0.06	-	0.35	0.12	0.33	0.00
	(0.31)	(0.16)	(0.24)	-	(0.48)	(0.33)	(0.47)	(0.06)
Age (in years)	32.81	30.43	31.11		34.99	32.30	34.74	25.00
	(10.51)	(8.53)	(11.30)		(11.74)	(6.47)	(9.92)	(6.24)
Working	0.84	0.61	0.64		0.27	0.27	0.23	0.00
	(0.37)	(0.50)	(0.48)		(0.44)	(0.45)	(0.42)	(0.00)
N	94	23	56	-	305	107	292	3

Note: Panels A and B report the type of relationship of the top two rank-ordered peers of the husband and the wife surveyed at baseline, respectively. In Panel C, the sample is restricted to the two treated (and surveyed) peers of wives only in the T2 group. This includes all peers recommended by the wives in T2 for treatment, including those reported at baseline. The network characteristics in Panel C are reported at intervention, approximately 3-6 months after the baseline. Panels A, B, and C are based on the network data for 1198 husbands, 1123 wives (all arms) and 420 wives in T2, respectively. Standard errors in parentheses.

Table 2A.6: Impact of treatment on labor market outcomes (6 months after intervention)

	Work Status		Workdays (per week)		Work hours (per day)		Earnings (per month)	
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1 (without network)	0.030	-0.031	0.133	-0.081	0.101	-0.240	0.181	-1.109*
	(0.022)	(0.030)	(0.176)	(0.238)	(0.180)	(0.268)	(0.348)	(0.569)
T2 (with network)	0.015	-0.011	0.171	0.069	0.070	-0.059	0.088	-0.243
	(0.019)	(0.027)	(0.160)	(0.224)	(0.155)	(0.256)	(0.314)	(0.541)
Baseline Y	0.341	0.338*	0.492***	0.336***	0.623***	0.307***	0.281***	0.151***
	(0.359)	(0.180)	(0.097)	(0.116)	(0.126)	(0.097)	(0.055)	(0.054)
p-value [T1=T2]	[0.51]	[0.51]	[0.83]	[0.55]	[0.86]	[0.51]	[0.79]	[0.12]
Observations	1,401	1,402	1,401	1,402	1,401	1,402	1,401	1,402
R-squared	0.156	0.047	0.165	0.048	0.186	0.047	0.184	0.051
Mean Y	0.23	0.94	1.25	5.69	1.05	8.37	889.07	11515.43

Note: The dependent variable in columns (1)-(2) is an indicator variable that takes a value of one if an individual is working in the reference period and zero otherwise. In columns (3)-(4) and (5)-(6) the dependent variable is the IHS transformation of the number of days worked in a week and the number of hours worked in a day, respectively. In columns (7)-(8) the outcome is the IHS transformation of the monthly earnings in the reference period. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the corresponding dependent variable in levels for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.7: Heterogeneity by demographics in the impact of treatment on work status

(> 1 year after intervention)

	Poor		SC-ST		Hindu		Education		Spouse Education		Parents		Young	
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
T1 (without network)	-0.067	0.003	-0.050	-0.027	-0.052	0.011	-0.094**	-0.011	-0.105**	-0.043	-0.083**	0.015	-0.133***	0.001
	(0.042)	(0.029)	(0.031)	(0.029)	(0.062)	(0.040)	(0.040)	(0.030)	(0.047)	(0.030)	(0.036)	(0.029)	(0.035)	(0.027)
T2 (with network)	-0.028	0.042	0.044	0.029	0.064	0.064**	-0.002	0.027	-0.009	0.032	0.039	0.047*	0.008	0.067***
	(0.041)	(0.029)	(0.040)	(0.027)	(0.067)	(0.028)	(0.039)	(0.031)	(0.045)	(0.027)	(0.041)	(0.028)	(0.043)	(0.023)
T1 x Z	0.037	-0.036	0.013	0.022	0.008	-0.035	0.090**	-0.011	0.092**	0.046	0.088**	-0.073	0.171***	-0.060
	(0.043)	(0.041)	(0.045)	(0.047)	(0.066)	(0.047)	(0.039)	(0.038)	(0.046)	(0.043)	(0.043)	(0.049)	(0.039)	(0.043)
T2 x Z	0.078*	0.003	-0.057	0.035	-0.057	-0.026	0.035	0.025	0.042	0.019	-0.043	-0.009	0.022	-0.075**
	(0.042)	(0.035)	(0.050)	(0.042)	(0.069)	(0.035)	(0.041)	(0.031)	(0.051)	(0.032)	(0.045)	(0.046)	(0.048)	(0.037)
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,376	1,375	1,377	1,377	1,377	1,377
R-squared	0.183	0.054	0.183	0.053	0.182	0.053	0.184	0.053	0.184	0.054	0.187	0.056	0.191	0.056
Estimate T1 (Z=1)	-0.03	-0.032	-0.037	-0.005	-0.044	-0.024	-0.004	-0.021	-0.013	0.003	0.005	-0.058*	0.038	-0.059*
Estimate T2 (Z=1)	0.05	0.046*	-0.013	0.064**	0.008	0.038*	0.033	0.051**	0.033	0.052**	-0.004	0.038	0.03	-0.008

Note: The dependent variable is an indicator for work status. It takes a value of one if an individual is working in the reference period and zero otherwise. Z denotes an individual characteristic measured at baseline – *Poor* is an indicator variable for individuals in the bottom tercile of asset index distribution; *SC-ST* is an indicator for individuals belonging to the SC or ST category; *Hindu* indicates individuals following the Hindu religion; *Education* and *Spouse Education* indicate individuals who report own and spouse education level, respectively, to be above primary; *Parent* indicates individuals with children below 5 years of age at baseline and *Young* is an indicator variable for individuals in the 15-30 age category. For our main categories ($Z = 1$), these characteristics equal one. For the base categories ($Z = 0$), these equal zero. The first two rows report the regression coefficients for T1 and T2 for the base categories while the third and fourth rows report the heterogeneous treatment effects for T1 and T2, respectively, by the characteristic. The last two rows 'Estimate (Z=1)' report the estimated coefficients for the main categories for T1 and T2, respectively. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.8: The impact of treatment on own work status by own and peers' gender attitudes ($>$ 1 year after intervention)

	Own Attitudes				Peers' Attitude			
	Regressive gender roles		Progressive work attitudes		Regressive gender roles		Progressive work attitudes	
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1 (without network)	-0.045*	-0.017	-0.047	-0.012	-0.048	-0.019	-0.084**	-0.005
	(0.027)	(0.022)	(0.037)	(0.024)	(0.031)	(0.038)	(0.038)	(0.028)
T2 (with network)	0.024	0.043*	0.017	0.041*	0.089**	0.064*	-0.052	0.048*
	(0.034)	(0.023)	(0.040)	(0.023)	(0.042)	(0.033)	(0.038)	(0.027)
T1 x Z	0.011	-0.004	0.008	-0.024	-0.011	0.002	0.056	-0.038
	(0.053)	(0.056)	(0.043)	(0.042)	(0.057)	(0.058)	(0.047)	(0.055)
T2 x Z	-0.014	0.005	0.002	0.005	-0.125**	-0.034	0.150***	-0.003
	(0.056)	(0.051)	(0.050)	(0.034)	(0.061)	(0.043)	(0.046)	(0.039)
Observations	1,376	1,373	1,376	1,370	1,016	1,011	1,016	1,012
R-squared	0.183	0.053	0.182	0.054	0.199	0.058	0.200	0.057
Estimate T1 (Z=1)	-0.034	-0.021	-0.04	-0.036	-0.059	-0.017	-0.027	-0.043
Estimate T2 (Z=1)	0.01	0.048	0.02	0.046	-0.036	0.03	0.098***	0.045

Note: The dependent variable is an indicator for own work status. It takes a value of one if an individual is working and is zero otherwise. All attitudes, 'Own' (columns (1)-(4)) and the average over 'Peers' (columns (5)-(8)), are measured at baseline. *Regressive gender roles* indicates relatively restrictive gender attitudes (takes a value of one for above median Z-score of regressive attitudes and is zero below median values) and *Progressive work attitudes* indicates relatively liberal attitudes towards women's outside work (takes a value of one for above median Z-score of progressive attitudes and is zero below median values) . For our main categories ($Z = 1$), these characteristics equal one and zero for the base categories ($Z = 0$). The first two rows report the regression coefficients for T1 and T2 for the base categories while the third and fourth row report the heterogeneous treatment effects for T1 and T2, respectively, by these characteristics. The last two rows 'Estimate (Z=1)' report the estimated coefficients for the main categories for T1 and T2, respectively. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.9: Impact of treatment on type of earnings (> 1 year after intervention)

Earnings Type	Salary				Piece-rate				Daily wage			
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	-0.009	0.097***			-0.002	-0.062***			-0.002	-0.049***		
	(0.014)	(0.028)			(0.013)	(0.019)			(0.002)	(0.014)		
T1 (without network)			-0.017	0.068**			-0.016	-0.060***			-0.003	-0.049***
			(0.017)	(0.030)			(0.015)	(0.021)			(0.003)	(0.014)
T2 (with network)			-0.001	0.128***			0.014	-0.063***			-0.002	-0.050***
			(0.017)	(0.036)			(0.016)	(0.020)			(0.002)	(0.013)
Baseline Y	0.374***	0.276***	0.372***	0.276***	0.264***	0.228***	0.267***	0.229***	0.001	0.077	0.001	0.077
	(0.074)	(0.049)	(0.074)	(0.049)	(0.053)	(0.046)	(0.053)	(0.046)	(0.001)	(0.062)	(0.001)	(0.062)
p-value [T1=T2]			[0.38]	[0.09]			[0.05]	[0.86]			[0.74]	[0.66]
Observations	1,321	1,254	1,321	1,254	1,321	1,254	1,321	1,254	1,321	1,254	1,321	1,254
R-squared	0.227	0.243	0.227	0.245	0.110	0.112	0.113	0.112	0.009	0.058	0.009	0.058
Mean Y	0.09	0.58	0.09	0.58	0.08	0.07	0.08	0.07	0	0.01	0	0.01

Note: The dependent variable is an indicator variable for different types of wage earnings. In Columns(1)-(4), it takes a value of one if an individual is paid a fixed salary and zero otherwise. Similarly, columns (5)-(8) and Columns (9)-(12) are indicator variables for piece-rate and daily wages, respectively. Columns (1)-(2), (5)-(6) and (9)-(10) report the combined treatment effect using equation (3B.1) while columns (3)-(4), (7)-(8) and (11)-(12) report the treatment-wise effect for equation (2.2), by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 2A.10: Robustness (Balanced Sample): Impact of treatment on employment outcomes (> 1 year after intervention)

	Work status		Workdays (per week)		Work hours (per day)		Earnings (monthly)	
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1 (without network)	-0.042	-0.021	-0.399*	0.398	-0.433**	0.355	-0.770*	0.849
	(0.027)	(0.021)	(0.205)	(0.275)	(0.209)	(0.311)	(0.413)	(0.625)
T1 (without network)	0.018	0.044**	0.130	0.705**	0.083	0.765**	0.188	1.586**
	(0.029)	(0.020)	(0.223)	(0.271)	(0.225)	(0.308)	(0.446)	(0.626)
Baseline Y	0.921***	0.149	0.418**	0.155	0.461***	0.205**	0.257***	0.094**
	(0.041)	(0.204)	(0.160)	(0.102)	(0.168)	(0.083)	(0.085)	(0.044)
p-value [T1=T2]	[0.03]	[0]	[0.01]	[0.08]	[0.01]	[0.04]	[0.02]	[0.08]
Observations	1,364	1,364	1,364	1,364	1,364	1,364	1,364	1,364
R-squared	0.188	0.054	0.186	0.049	0.191	0.050	0.196	0.048
Mean Y	0.23	0.94	1.23	5.68	1.03	8.36	879.67	11539.27

Note: The dependent variable in columns (1)-(2) is an indicator variable that takes a value of one if an individual is working in the reference period and is zero otherwise. Columns (3)-(4) report the IHS transformed workdays in a week, columns (5)-(6) list IHS transformed hours of work in a day and columns (7)-(8) report the IHS transformation of monthly earnings. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable in levels for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 2A.11: Robustness: Internal Validity

	Responders			Attritors			Differences			
							Responders		Attritors	
	Control	T1	T2	Control	T1	T2	T1-C	T2-C	T1-C	T2-C
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Work Status									
Endline 1	0.59	0.59	0.6	1	0.69	0.75	[0.84]	[0.46]	[0.37]	[0.49]
Endline 2	0.59	0.59	0.61	0.69	0.59	0.55	[0.72]	[0.34]	[0.56]	[0.37]
	Panel B: Earnings (Monthly)									
Endline 1	6205.7	6189	5823.73	4500	4500	5000	[0.98]	[0.52]	[1]	[0.90]
Endline 2	6204.13	6149.75	5771.89	6061.54	5909.09	6544.64	[0.94]	[0.48]	[0.94]	[0.86]

Note: The dependent variable in Panel A and Panel B are the average work status and monthly earnings at baseline. Work status is an indicator variable that takes a value of one if an individual is working in the reference period and zero otherwise. Columns (1)-(3) report the mean for the responders (i.e., non-attriters for whom data was collected at respective endlines) while columns (4)-(6) report it for the attriters (i.e., individuals surveyed at baseline who couldn't be reached for data collection at respective endlines). In columns (7)-(8), we report the p-values of the test of mean differences between the two treatment arms - T1 (column (7)) and T2 (column (8)) and control group for the responders, while the corresponding p-values for attriters are in columns (9)-(10).

Table 2A.12: Heterogeneity in the impact of treatment on work status by network overlap ($>$ 1 year after intervention)

	Relatives		Neighbours	
	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)
T1 (without network)	-0.044	-0.018	-0.044	-0.018
	(0.027)	(0.020)	(0.027)	(0.020)
T2 $\times Overlap = 0$	0.011	0.034	0.005	0.037*
	(0.031)	(0.022)	(0.030)	(0.021)
T2 $\times Overlap = 1$	0.033	0.064***	0.089	0.078***
	(0.041)	(0.023)	(0.063)	(0.021)
Observations	1,377	1,377	1,377	1,377
R-squared	0.182	0.053	0.183	0.053

Note: The dependent variable is an indicator for overall work status, which takes a value of one if an individual is working in the reference period and zero otherwise. The first row reports the estimate for treatment without network (T1). The second and the third row report the estimates for treatment with network (T2) by no overlap in the treated network of wife and husband and those who have an overlap, respectively. The overlap is captured by the presence of treated non-co-resident family members (columns (1) - (2) and neighbors (columns (3) - (4)) in the social network of the wife. If such peers exist in the wife's network (also relatives/neighbors of the husbands) then the variable 'Overlap' takes value one and zero otherwise. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.13: Heterogeneity in the impact of treatment on work status by structure of network ($>$ 1 year after intervention)

Network Type (Z)	Non-co-resident Family		Friends		Neighbors		Co-workers	
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1 (without network)	0.070	-0.025	-0.056**	0.019	-0.064**	-0.045*	-0.047*	-0.018
	(0.070)	(0.031)	(0.026)	(0.027)	(0.029)	(0.023)	(0.026)	(0.022)
T2 (with network)	0.160**	0.032	0.003	0.055**	-0.011	0.042*	0.015	0.045**
	(0.067)	(0.027)	(0.029)	(0.025)	(0.034)	(0.023)	(0.029)	(0.021)
T1 $\times$ Proportion Z	-0.151*	0.021	0.362	-0.097*	0.097	0.169**	0.762	0.002
	(0.080)	(0.056)	(0.227)	(0.050)	(0.074)	(0.072)	(0.627)	(0.103)
T2 $\times$ Proportion Z	-0.194**	0.030	0.381**	-0.027	0.131	0.014	0.806	-0.037
	(0.078)	(0.050)	(0.191)	(0.043)	(0.080)	(0.069)	(0.791)	(0.070)
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377
R-squared	0.187	0.054	0.186	0.055	0.184	0.057	0.184	0.054

Note: The dependent variable is an indicator for own work status. It takes value one if the individual is working and zero otherwise. Columns (1)-(2) report the heterogeneity estimates by the proportion of the baseline social network consisting of non-co-resident family members, columns (3)-(4) by proportion of friends, columns (5)-(6) by neighbors and columns (7)-(8) by co-workers. The first and second rows report the regression coefficients for the non-network and network treatments while the third and fourth row report the heterogeneity in the treatment effects by the proportion of the network consisting of different types of peers. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.14: Impact of treatment on type of self-employment (> 1 year after intervention)

Employment Type	Own business manufacturing				Retail				Other Services			
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.019	-0.001			-0.004	-0.002			0.002	0.032*		
	(0.013)	(0.017)			(0.007)	(0.020)			(0.006)	(0.016)		
T1 (without network)			-0.006	-0.005			-0.009	0.006			0.000	0.031
			(0.011)	(0.017)			(0.007)	(0.023)			(0.006)	(0.019)
T2 (with network)			0.045**	0.002			0.001	-0.010			0.004	0.033*
			(0.019)	(0.021)			(0.009)	(0.022)			(0.007)	(0.020)
Baseline Y	0.069	0.110***	0.068	0.110***	0.190**	0.366***	0.189**	0.365***	0.074	0.258***	0.074	0.258***
	(0.059)	(0.037)	(0.059)	(0.037)	(0.089)	(0.047)	(0.088)	(0.047)	(0.047)	(0.043)	(0.048)	(0.043)
p-value [T1=T2]			[0]	[0.71]			[0.28]	[0.44]			[0.6]	[0.91]
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377
R-squared	0.057	0.057	0.070	0.058	0.070	0.211	0.071	0.211	0.030	0.089	0.031	0.089
Mean Y	0.08	0.11	0.08	0.11	0.01	0.11	0.01	0.11	0.03	0.11	0.03	0.11

Note: The dependent variable is an indicator variable for different types of self-employment. In Columns(1)-(4), it takes a value of one if an individual is self-employed in own business manufacturing and zero otherwise. Similarly, Columns (5)-(8) and Columns(9)-(12) are indicator variables for self-employment in retail and other services (e.g. salon), respectively. Columns (1)-(2), (5)-(6) and (9)-(10) report the combined treatment effect using equation (3B.1) while Columns (3)-(4), (7)-(8) and (11)-(12) report the treatment-wise effect for equation (2.2), by gender. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.15: Heterogeneity in self-employment status of wives by self-employment of her peers

	All peers (1)	Female peers (2)	Male peers (3)
T1 (without network)	-0.023	-0.023	-0.013
	(0.016)	(0.015)	(0.015)
T2 (with network)	0.029	0.032	0.045*
	(0.022)	(0.021)	(0.023)
T1 × Z	0.079*	0.142**	-0.003
	(0.041)	(0.057)	(0.036)
T2 × Z	0.096**	0.140**	0.013
	(0.046)	(0.054)	(0.057)
Observations	1,377	1,377	1,377
R-squared	0.087	0.091	0.083
Mean Y	0.12	0.12	0.12

Note: The dependent variable is an indicator variable that takes value one if the wife is self-employed in reference period and zero otherwise. Column (1) reports the heterogeneity in wife's self-employment at Endline 2 (one year after the intervention) by the proportion of peers contemporaneously (at Endline 2) engaged in self-employment (Z) and columns (2)-(3) report it by gender of the peer. The first and second rows report the regression coefficients for non-network and networks treatments while the third and fourth row report the heterogeneity in the treatment effects by the proportion of self-employed peers (Z) in the social network of the wife. 'Mean Y' denotes the mean value of the dependent variable for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.16: Impact of treatment on attitude towards gender roles (> 1 year after intervention)

	Attitude 1				Attitude 2				Attitude 3				Attitude 4			
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment	-0.441***	-0.471***			-0.190*	-0.239***			-0.202**	-0.102			0.091	0.033		
	(0.115)	(0.072)			(0.110)	(0.080)			(0.084)	(0.071)			(0.096)	(0.110)		
T1 (without network)			-0.452***	-0.453***			-0.272**	-0.303***			-0.168*	-0.025			-0.007	-0.114
			(0.143)	(0.085)			(0.136)	(0.097)			(0.093)	(0.073)			(0.102)	(0.117)
T2 (with network)			-0.430***	-0.489***			-0.104	-0.171*			-0.237**	-0.183*			0.192	0.189
			(0.136)	(0.106)			(0.120)	(0.102)			(0.099)	(0.097)			(0.116)	(0.130)
Baseline Y	0.053	0.113***	0.052	0.112***	0.021	0.002	0.023	0.001	0.066*	0.010	0.066*	0.012	-0.034	0.006	-0.036	0.001
	(0.036)	(0.040)	(0.036)	(0.040)	(0.038)	(0.030)	(0.037)	(0.029)	(0.039)	(0.027)	(0.039)	(0.027)	(0.032)	(0.032)	(0.032)	(0.032)
p-value [T1=T2]			[0.89]	[0.77]			[0.21]	[0.27]			[0.47]	[0.1]			[0.06]	[0.01]
Observations	1,376	1,377	1,376	1,377	1,377	1,376	1,377	1,376	1,376	1,375	1,376	1,375	1,377	1,375	1,377	1,375
R-squared	0.056	0.065	0.056	0.065	0.024	0.034	0.028	0.037	0.025	0.007	0.026	0.011	0.017	0.009	0.023	0.024
Mean Y	-0.1	0.09	-0.1	0.09	0.21	-0.22	0.21	-0.22	-0.02	0.02	-0.02	0.02	0.05	-0.1	0.05	-0.1

Note: The dependent variables are the standardised Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the responses to questions on gender attitudes (Attitude1: It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family; Attitude2: It is more important for a wife to help her husband's career than to have one herself; Attitude3: When a mother works for pay, the children suffer, Attitude4: A working mother cannot establish just as warm and secure a relationship with her children as a mother who does not work). A higher value represents gender progressive attitudes. Columns (1)-(4), (5)-(8), (9)-(12) and (13)-(16) report the coefficients for first, second, third and fourth attitude, respectively. Columns (1)-(2) report the combined treatment effect using equation (3B.1) while Columns (3)-(4) report it for equation (2.2), by gender for the first Attitude. Similarly, the subsequent columns report the result for the second, third and fourth Attitude. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at Baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2A.17: Impact of treatment on attitudes towards women's outside work (> 1 year after intervention)

	Attitude 1				Attitude 2				Attitude 3				Attitude 4			
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment	0.132*	-0.075			0.148**	0.082			-0.105*	-0.178**			0.143**	-0.002		
	(0.069)	(0.068)			(0.057)	(0.060)			(0.063)	(0.075)			(0.065)	(0.055)		
T1 (without network)			0.215***	-0.012			0.128**	0.019			-0.072	-0.138*			0.150**	-0.030
			(0.071)	(0.078)			(0.063)	(0.071)			(0.074)	(0.081)			(0.068)	(0.068)
T2 (with network)			0.047	-0.142			0.169***	0.147**			-0.138*	-0.221**			0.135*	0.028
			(0.089)	(0.087)			(0.061)	(0.065)			(0.073)	(0.086)			(0.070)	(0.062)
Baseline Y	0.048	0.082***	0.048	0.081***	0.060*	0.114***	0.059*	0.115***	0.099***	0.115***	0.099***	0.118***	0.017	0.018	0.017	0.020
	(0.034)	(0.031)	(0.034)	(0.030)	(0.035)	(0.029)	(0.035)	(0.028)	(0.032)	(0.030)	(0.032)	(0.030)	(0.023)	(0.037)	(0.023)	(0.037)
p-value [T1=T2]			[0.04]	[0.17]			[0.39]	[0.06]			[0.38]	[0.26]			[0.76]	[0.42]
Observations	1,377	1,377	1,377	1,377	1,376	1,377	1,376	1,377	1,376	1,373	1,376	1,373	1,377	1,374	1,377	1,374
R-squared	0.034	0.026	0.039	0.029	0.037	0.044	0.038	0.047	0.046	0.051	0.046	0.052	0.020	0.014	0.020	0.014
Mean Y	0.02	0	0.02	0	0.11	-0.12	0.11	-0.12	0.28	-0.27	0.28	-0.27	-0.07	0.07	-0.07	0.07

Note: The dependent variables are the standardised Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the responses to questions on gender attitudes. (Attitude1: In your opinion, is it acceptable for an adult woman to travel outside the locality if she wants to?; Attitude2: In your opinion, should an adult woman work outside of home if she wants to?; Attitude3: Do you approve of a married woman earning money if she has a husband capable of supporting her?; Attitude4: In your opinion, if the wife is working outside the home, should the husband help her with household/care duties?). A higher value represents gender progressive Attitudes. Columns (1)-(4), (5)-(8), (9)-(12) and (13)-(16) report the coefficients for first, second, third and fourth Attitude, respectively. Columns (1)-(2) report the combined treatment effect using equation (3B.1) while Columns (3)-(4) report it for equation (2.2), by gender for the first Attitude. Similarly, the subsequent columns report the result for the second, third and fourth Attitude. The p-values correspond to test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the dependent variable for the control group at Baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Chapter 3

The Gendered Effects of Droughts: Production Shocks and Labor Response in Agriculture[1]

3.1 Introduction

Climate change has not only resulted in a rise in average temperatures, but it has also increased the incidence and severity of extreme weather events such as droughts and floods (Schiermeier, 2018). Such weather shocks are predicted to rise further if climate change continues unabated (Hsiang and Kopp, 2018; IPCC, 2021). Amongst all economic sectors, agriculture is likely to face the greatest brunt of increasing rainfall uncertainty since more than 75% of the world's cropped area is rain-fed. Weather shocks resulting from extreme rainfall are, thus, likely to make agricultural incomes and employment prone to productivity risks - a greater concern in developing countries where agricultural systems are largely rain-fed and are also managed by some of the poorest communities. The absence of social insurance and incomplete credit markets in low-income economies underlies the importance of labor as a resource for individuals to cope

[1] This paper is joint work with Farzana Afridi (ISI-Delhi) and Kanika Mahajan (Ashoka University) and is published in Labour Economics. Refer to Afridi et al. (2022b).

with such shocks. Additionally, negative short-term productivity shocks such as droughts can potentially exacerbate extant gender differences in labor market outcomes when women's access to off-farm work opportunities is constrained by social factors such as low mobility.

India, with 40% of its workforce employed in the agriculture sector, has experienced an increased incidence, duration and intensity of droughts, over the last century (Figure 3.1).[2] In this paper, we combine high frequency, individual-level panel data capturing monthly labor supply and seasonal migration during 2010-14 across eight agro-climatic zones of India to analyze the role of labor markets in mitigating the impact of adverse agricultural production shocks due to droughts. Specifically, we examine the short-term impact of deficient rainfall on individuals' overall labor force participation, employment on the farm and diversification towards the non-farm sector on both the extensive and intensive margins in rural areas. In a context where men are often better placed to take advantage of available coping mechanisms through their access to other work via seasonal migration, we assess these labor responses by gender. Thus, we also uncover the mechanisms underlying the gender-differentiated impacts on employment.

Our results indicate a fall in women's labor force participation relative to that of men's in the event of a drought. We find that women are 7.1% less likely to be employed but 80% more likely to seek work than men in a drought year. On the intensive margin, women's employment relative to that of men's is lower by 19%. This is because men increase their days spent on non-farm work by 22.5%, but there is no significant impact on women's engagement in the non-farm sector. Consequently, women's non-farm workdays relative to men's fall by 20.1% in drought years. At the same time, women spend 29.4% more days seeking work, relative to men, when faced with a drought shock. Hence, while men diversify to non-farm sector jobs to cope with droughts, women continue to stay in the farm sector, even as they seek work and their real farm wage earnings (conditional on being employed on the farm) and real daily wage rates fall by 38.1% and 11.4%, respectively.

We find that the lack of substitution towards the non-farm sector in response to a drought by women is due to their restricted mobility. Women are less likely than men to work outside the village or migrate, on average, and more so in drought years. The probability that men take up work outside the village and migrate during a drought increases by 1.7 percentage points (pp)

[2] See: Indian Meteorological Department (IMD report 2020). A drought is defined to occur for a grid point when rainfall in the main monsoon season (June-September for India) lies in the first two deciles of the long term rainfall distribution of that grid point.

and 0.8 pp, respectively, but there is no impact on women's workplace location. Men's higher mobility translates into 18.6% higher non-farm earnings for them relative to women, in the event of a drought.

We find suggestive evidence for social costs emanating from rigid gender norms that place a higher burden of home production and care work on women, as well as concerns around women's sexual 'purity' that inhibit their access to alternative sources of employment beyond their immediate vicinity, as possible explanations behind their lower mobility. Not surprisingly, our analysis shows that women who are younger, married and with young children are not only less likely to divert their labor to the non-farm sector, but are also less likely to migrate relative to men with the same characteristics. These findings are robust to individuals' unobserved heterogeneity, seasonality, secular and village specific trends. They are also held up by nationally representative district-level panel data.

It is well acknowledged that reliance on insurance is mostly absent, while credit markets are incomplete, in agricultural economies (Morduch, 1995). Hence, utilization of labor, specifically a diversification to the non-farm sector, has been documented as a coping strategy adopted by agricultural households during economic shocks that adversely affect crop yields and incomes (Rose, 2001; Minale, 2018; Colmer, 2021; Grabrucker and Grimm, 2021; Blakeslee et al., 2020; Branco and Feres, 2021).[3]

Studies also document a fall in real daily farm wages due to a reduction in demand for labor during a drought, with a larger wage reduction in areas with lower access to non-farm opportunities (Jayachandran, 2006; Mueller and Osgood, 2009; Auffhammer et al., 2012; Mahajan, 2017). Naturally, households often migrate when incomes and livelihoods are adversely affected due to weather shocks like deficient rainfall (see Badiani and Safir (2008); Marchiori et al. (2012); Morten (2019), among many others), heat stress (Cai et al., 2016), floods (Giannelli and Canessa, 2022) and storms (Gröger and Zylberberg, 2016).[4]

[3]Absent this labor reallocation, the economic losses can be enormous – up to 69% higher as estimated by Colmer (2021) for temperature-driven adjustments using data from Indian firms. Other coping mechanisms include – diversifying income sources to the non-farm sector (Ito and Kurosaki, 2009); ex-ante cultivating low-risk crops (Morduch, 1995); varying planting timing (Kala, 2017); investing in increased irrigation (Taraz, 2017) and using drought-resistant seeds - these strategies are however often more costly and less likely to be adopted in developing countries (Kristjanson et al., 2017). See Dell et al. (2014) for a review of studies that assess the effects of precipitation and temperature shocks on agricultural yield and productivity as well as adaptation by farmers.

[4]Emerick (2018), using district-level data from India shows that above-normal precipitation increases the share of non-farm sector employment. This is driven by increased local demand for goods that attract labor to the non-farm sector. Thus, when estimating the effects of negative precipitation shocks on employment outcomes, we control for positive precipitation shocks to allow for differential changes in sectoral employment in periods of both low productivity shocks (due to distress) and high productivity shocks (due to increased local demand).

However, much less is known about the individual, specifically gender-differentiated responses to these shocks. In the context of developing countries where women are generally less mobile and less likely to search widely for work (Heath and Mobarak, 2015; Andrabi et al., 2013), men may be better placed to cope with productivity shocks in agriculture and diversify into sectors less subject to weather shocks. But evidence of gender differences in labor response for smoothing the risk emanating from weather shocks, is almost absent, with a few exceptions. Huang et al. (2020) use retrospective employment data for three years from rural China to examine labor re-allocation, in response to temperature and precipitation change, from farm to non-farm activities by gender at the province level. They find no differential impact in take up of non-farm work by gender due to such shocks. In Uganda, where men and women cultivate separate plots of land, Agamile et al. (2021) show that women diversify to more risky, commercial crops and away from subsistence farming while men allocate more time to off-farm labor employment during a drought. However, none of these papers addresses either individual or household level unobserved heterogeneity in assessing the response to climate shocks or explore the underlying mechanisms.[5]

While the existing literature largely focuses on how households diversify their income sources when farm productivity shrinks, we focus on the gender differences in individual decisions when struck by an adverse agricultural productivity shock. Second, and relatedly, unlike the aggregate geographical data used in most previous studies, we underline the potential gender-differentiated impact of climatic shocks such as droughts utilizing novel individual-level panel data over eight agro-climatic zones, collected at a monthly frequency. We are thus able to account for seasonal impacts that are relevant to the agricultural sector.

Furthermore, none of the existing studies provide mechanisms behind the observed gender-differentiated impacts. Our analysis uncovers the underlying mechanisms that can explain the lower likelihood of women substituting towards less risky, non-farm sector jobs, relative to men through detailed data on the nature of employment, place of work, and migration. Unlike most household surveys that capture employment details of only current members of the household and miss out on those members who are temporary migrants, our data allow us to investigate

[5] In the Indian context, Maitra and Tagat (2019) examine the gender-differential in the labor responses to rainfall shocks for self-employed and wage work at the district level, but not substitution towards the non-farm sector. They find that men increase their regular wage work in response to negative rainfall shocks while there is no change for women. Kochar (1999) finds evidence for consumption smoothing by cultivating households in the event of household crop income shocks (as opposed to an aggregate shock, such as rainfall) through diversification of labor to the non-farm sector, but only by men. Neither delves into the mechanisms that cause this gendered response, in general, or the location of non-farm work, specifically.

coping mechanisms from farm income losses through engagement in seasonal migration, and the extent to which men and women are able to access non-farm sources of employment through this channel. Our research, thus, also speaks to the literature on migration, by highlighting the role of seasonal migration as a coping mechanism and its potential in exacerbating the impact of weather shocks on gender equality (Cattaneo et al., 2019).[6]

Lastly, through our heterogeneity analyses of the individual-level data which exploits the age, marital status, and parenthood of an individual, we are able to show that social norms around the gendered nature of household production and women's purity place a cost on women's access to employment opportunities outside their village.

Indeed, we find suggestive evidence that public employment programs that provide work close to women's homes, not only mitigate production risks in agriculture in the short-run but also stem gender disparities in employment opportunities. Social norms, thus, can plausibly explain the observed gender-differentiated impacts of droughts in our context. This mechanism, to the best of our knowledge, has not been previously highlighted in the literature. While we do not find evidence in support of gender skill differentials or safety concerns, we are unable to test for gender-differentiated changes in demand for labor in the farm and non-farm sectors, due to data constraints.

The above findings are in contrast to the theoretical prediction and empirical evidence which shows that women's employment rate increases in response to negative household level idiosyncratic income shocks in low-income economies (Attanasio et al., 2005; Skoufias and Parker, 2006; Sabarwal et al., 2011). Our findings show that while women are more likely to seek work due to negative aggregate income shocks, their employment may not increase if their labor mobility is limited. Additionally, climatic shocks may have long-term effects. Our cross-sectional estimates indicate that gender gaps in non-farm employment and migration are larger in villages facing higher risks from rainfall variability, suggesting that men may permanently shift their occupational structure to the less risky non-farm sector. Indeed, Albert et al. (2021) finds that regions facing increased frequency of droughts witness a shift in employment towards

[6]There is, however, no consensus in this literature since the search for alternative locations for residence can increase while credit constraints can decrease permanent migration. Dillon et al. (2011) and Gray and Mueller (2012) find that men are more likely to permanently migrate in response to temperature increases in Nigeria and droughts in Ethiopia. On the other hand, Baez et al. (2017) find increased permanent migration by women in response to heat exposure in the Latin America and Caribbean region. The responses can also vary by the nature of the negative productivity shock such as harvest losses vs earthquakes (Halliday, 2012). Importantly, while the existing literature has largely focused on permanent migration, our main interest in this paper is to look at the channel of seasonal migration for alternative employment in the face of shock.

the non-farm sector and an increase in population outflows over two decades in Brazil. In contrast, Liu et al. (2021) and Jessoe et al. (2018) show that long-term temperature increases reduce non-farm employment share and lower rural-urban migration rates in India and Mexico, respectively. Our findings, thus, call for further research on the longer-term effects of weather shocks, from a gender perspective.

The remainder of the paper is organized as follows. In the next section, we set up the conceptual framework. Section 3.3 describes the data used in the analysis and discusses the estimation strategy. The results and their robustness are presented in Section 3.4. We discuss the mechanisms that underlie our findings in Section 3.5, and conclude in Section 3.6.

3.2 Conceptual Framework

We develop a simple theoretical framework for analysing labor supply decisions in response to production shocks in an agrarian economy. We assume two sectors - farm (a) and non-farm (n), and two types of agents (g) - female (f) and male (m). A representative agent is endowed with one unit of time that can be allocated to three activities: farm work (l_a), non-farm work (l_n) and leisure ($1 - l_a - l_n$). The agent obtains utility from consumption of farm good (c_a), non-farm good (c_n) and leisure ($1 - l_a - l_n$) and takes prices and wages as given.

We build on the empirical evidence around restricted labor mobility of women by including social costs associated with an agent working in the non-farm sector in our framework. Agents internalise these social costs, deriving disutility from participation in the non-farm sector, which varies by gender, with women bearing a higher disutility. To elaborate, while farm work is usually close to home in agrarian economies, non-farm work is typically located at a distance. In our data, for instance, the average distance to farm work (conditional on farm employment) in a month, including seasonal migration, is 75 km while it is 3832 km for non-farm work (conditional on non-farm employment). This indicates the important role played by seasonal migration for access to non-farm jobs. Even if we exclude migration, a large gap persists in the average distance to farm work (4 km) and non-farm work (212 km).

Thus, social costs can arise due to the stigma associated with women's participation in work that reduces their time at home (due to increased travel times) – a consequence of social norms around the gendered division of labor at home wherein women are expected to be primary caregivers (Afridi et al., 2019; Heath and Mobarak, 2015; Andrabi et al., 2013).[7] In addition,

[7] Across the world, women spend triple the time on unpaid care work than men, ranging from 1.5-2.2 in North

notions about women's sexual 'purity' can cause stigma if women are likely to interact with men (other than family members) while travelling to work or at work (Dean and Jayachandran, 2019; Eswaran et al., 2013). This can lead to higher social costs for non-farm work for women because such work is predominantly male-dominated in India, a feature of the Indian labor market we discuss later.

The utility maximization problem for an agent, is thus, given by:

$$\max_{c_a, c_n, l_a, l_n} U_g = u_g\left(c_a, c_n, 1 - l_a - l_n\right) - v_g\left(l_n\right) \tag{B.1}$$

subject to,

$$c_a + c_n p \leq l_a w_a + l_n w_n \tag{B.2}$$

where $v_g\left(l_n\right)$ captures dis-utility due to the social cost of participation in the non-farm sector. The utility function is assumed to be well behaved, i.e., increasing at a decreasing rate in all the arguments. The price of the farm good is normalised to one, while p denotes the price of the non-farm good. w_a and w_n are the wage rates in the farm and the non-farm sector, respectively, with the assumption that $w_a < w_n$. We consider the extreme case where only women face dis-utility from working in the non-farm sector.[8]

On the production side, the farm production function is given by:

$$A = \theta B^{\epsilon} L_a^{1-\epsilon} \tag{B.3}$$

where θ is the productivity parameter, B denotes the land used in production, L_a is total labor employed on the farm and ϵ is the share parameter.[9]

A negative productivity shock to the farm sector denoted by D, specifically drought, reduces θ. Consequently, this reduces the profit maximising equilibrium labor demand ($\frac{dL_a}{dD} < 0$) and depresses wage rates ($\frac{dw_a}{dD} < 0$). The detailed proofs are presented in Appendix 3.A.A. We

America and Europe to 6-6.8 times in the Middle East, North Africa, and South Asia (OECD Report). Time Use Survey for India (2018-19) shows that women spend eight times more time on household and care work than men (Hindustan Times). Further, in a recent survey by the PEW center, around 40% respondents in India reportedly prefer a marriage in which the husband provides for the family and the wife takes care of home and children as compared to 23% across the 34 countries surveyed in 2019. Among other low-middle income countries - Philippines, Kenya, and Nigeria - this proportion stood at 32%, 20%, and 33%, respectively.

[8] We find similar results if we instead assume that both the sexes incur this cost with women bearing a higher cost.

[9] We assume only one type of labor in this simple theoretical exposition, i.e., male and female labor are perfect substitutes. This implies that both types of labor get the same wage rate (w_a). This assumption is only for simplification of the theoretical exposition. We find similar results, albeit under some additional assumptions, when using a production function where male and female labor are imperfect substitutes.

further assume that production in the non-farm sector is independent of negative agricultural productivity shocks such as a drought.[10]

The solution to the utility maximization problem gives us the labor supply responses during a productivity shock to the farm sector (see Appendix 3.A.A for details). We are interested in the gender gap in these responses, which are expressed as follows:

$$\frac{dl_{af}}{dD} - \frac{dl_{am}}{dD} = \left(\frac{R+S}{H+Z} - \frac{R}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{B.4}$$

$$\frac{dl_{nf}}{dD} - \frac{dl_{nm}}{dD} = \left(\frac{J}{H+Z} - \frac{J}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{B.5}$$

The terms H, R, S, J and Z, defined in Appendix 3.A.A, are a collection of double derivatives of the utility function. One can sign these expressions under certain parametric assumptions. All plausible cases under which women's diversification to the non-farm sector employment could be restricted, while men move to the non-farm sector, when a drought occurs, are discussed in the Appendix. For simplicity of exposition, here we discuss the case when H>0. Under this case, it can be shown that R<0 and J>0, which implies that $\frac{dl_{am}}{dD} < 0$ and $\frac{dl_{nm}}{dD} > 0$, i.e., men diversify from the farm to the non-farm sector during a drought. The corresponding sign for female farm labor supply ($\frac{dl_{af}}{dD}$) depends on the values of S and Z which are associated with the social costs. While the sign of Z depends on the shape of the dis-utility function, the direction of S is ambiguous. Therefore, the direction of change in farm work for women in response to a drought can be either negative or positive, depending on the relative magnitude of these terms. This makes the relative effect of drought on women's versus men's farm labor employment ambiguous in equation (B.4).

Next, we look at the relative effect of drought on non-farm labor response by women versus men in equation (B.5). Given H>0, the sign of this term depends only on the sign of Z —when Z is positive, i.e., for a convex dis-utility function, the increase in the non-farm workdays of women would be less than that of men when faced with a drought shock. In this case, the relative effect of drought on women's versus men's non-farm labor employment is negative in equation (B.5), i.e., women are less likely to increase supply to the non-farm sector in the event of a drought when compared to men.

Hence, dis-utility from participation in work located further away or when male dominated due to social costs can restrict women's labor mobility and diversification away from the more

[10] Again, this assumption is only for simplification of the theoretical exposition. In fact, as long as the effect of drought on the productivity in the non-farm sector is smaller than its effect on the farm sector, an assumption validated by evidence that weather shocks affect the farm sector more (Pachauri et al., 2014), our theoretical predictions go through.

risky farm sector. Women's limited mobility can, therefore, lead to gendered effects in labor response to climate shocks.

3.3 Data and Methodology

We now describe the data and variables used in our analysis.

3.3.1 Data

Individual labor market outcomes

We use five rounds of the Village Dynamics in South Asia (VDSA) longitudinal survey data collected by ICRISAT in India.[11] The VDSA study aims to understand the dynamics of agricultural development and rural poverty by following households in 30 villages (representative of the Semi-Arid Tropics (SAT) and Humid Tropics regions) across eight states of India.[12] Figure 3A.1 in the Appendix shows the location of the sampled villages, which cover eight of the twenty agro-climatic zones of India. Each round collects employment data for the entire agricultural year, i.e., from July of this year to June of the following year, for 40 households per village, at a monthly frequency. These households (30 cultivator and 10 landless households) are selected at the beginning of the survey through stratified random sampling based on operational landholding size.[13] Detailed information on sampled households' socio-economic characteristics, agricultural production and livelihoods are collected annually, at the beginning of each agricultural year in July.

The survey records employment-related details for every month of each year for each member of a sampled household, including temporary migrants.[14] We use data on all individuals aged 15 and above in the five latest rounds of the survey from 2010-2014.[15] We, thus, use an individual-

[11]For details see `http://vdsa.icrisat.ac.in/`.

[12]The SAT regions, characterised by highly variable, low-to-medium rainfall and lack of irrigation facilities include the states of Andhra Pradesh, Karnataka, Maharashtra, Madhya Pradesh and Gujarat. The Humid tropics with hot and humid summers in Eastern India include the states of Bihar, Jharkhand and Odisha. Data are available for 2005-14 for the SAT region and 2009-14 for the Humid Tropics.

[13]A cultivator household refers to farm households that crop a positive amount of land in a season in a year, where season is defined on the basis of the crop type cultivated by the household and operational holding is the sum of own and net leased/shared land. If a household moves out of the village permanently, it is replaced by a household belonging to the same category.

[14]To elaborate, households are visited every month by the enumerator to collect monthly employment information for individuals listed as household members at the beginning of the agricultural year.

[15]We do not use data from previous survey rounds which began in 2005 because employment data are available at a monthly frequency only from 2010 on-wards for both the regions.

level monthly employment panel, allowing us to account for the individual-level unobserved heterogeneity. Our sample consists of 5,931 individuals from 1,367 households, comprising a total of 279,935 individual-month year observations (see Table 3A.1 in the Appendix).[16] The average age of individuals in our sample is a little over 35 years, with over 7 years of completed education. Approximately 50% of these are women, 65% are married and 25% have a young child below the age of 10 years (Panel A, Appendix Table 3A.1). A household, on average, has 1.56 children and almost two women or men in the 15-65 age group. These households are quite poor with a durable asset ownership value of about Rs. 12,000 or USD 165 (Panel B, Appendix Table 3A.1). We also construct an asset index to capture household wealth through asset ownership in the initial year the household was surveyed.[17]

Table 3A.2 in the Appendix reports the definitions and the summary statistics for the key labor market variables used in the analyses of the individual level monthly employment data. The employment module in the survey records both labor market participation and the number of workdays for each member of the household, by the type of work undertaken - paid farm (as hired labor on others farm), family farm (as labor on farm cultivated by family), family livestock and non-farm. Here, non-farm includes all work in the non-farm sector whether it was done for a wage or in a self-employed activity, with no differentiation between the two in the VDSA data.

Panel A and B of Table 3A.2 in the Appendix show the summary statistics for the variables that capture employment on the extensive margin and on the intensive margin, respectively. Panel A shows that on average 81% of the sample is engaged in the labor market in a month. There is higher participation in overall farm work (paid farm (15%) and family farm (43%)) relative to non-farm work (30%). Conversely, we find higher workdays per month in non-farm (6.53) than farm (paid (2.05) and family (3.46)), as shown in Panel B. This highlights the difference in the intensity of work between the two sectors. Panel C indicates that monthly non-farm real earnings are higher than the monthly earnings of a hired or paid laborer in the farm sector.

These overall statistics, however, hide considerable gender differences in labor market participation and outcomes as shown in Table 3.1. The labor force participation rate (LFPR) for women on an average in any given month is 69% while that for men is 92%. Excluding the activity of taking care of family livestock, women's LFPR further falls to 53% while that

[16]Our data set is not balanced since new members join the pool when they cross the threshold of 15 years and there would also be deceased individuals over a span of five years, especially for the elderly population. Even with these constraints, of the individuals observed in 2010, 93% are present in 2011, 89% in 2012, 87% in 2013, and 82% in 2014.

[17]Further details on the construction of these variables are mentioned in the note to Appendix Table 3A.1.

for men becomes 85% in the VDSA data. This figure is quite close to the usual status (worked for at least 30 days in the last year) female LFPR of 46% and male LFPR of 82% obtained using employment data from the nationally representative National Sample Survey (NSS) on employment and unemployment conducted in 2011-12, for the eight states lying in the SAT and Eastern regions of India.[18] Thus, gender disparities in employment in the VDSA data and the nationally representative data for India are comparable for these regions.

This gender gap in employment rates is largely due to the difference in the non-farm sector employment rates of 12% and 47% for women and men respectively (Panel A, Table 3.1). In terms of employed workdays, women work less than men by almost half, again with considerable heterogeneity across sectors (Panel B, Table 3.1). On average, women spend more days per month in farm work at 4.84 days (paid (2.39) and family (2.45)) than in non-farm work (2.51 days).[19] Further, in both the farm as well as the non-farm sector, real earnings of men are higher than that of women (Panel C, Table 3.1). Notably, the gender gap in earnings is much higher in the non-farm sector, with earnings of men eight times that of women. This is partly due to the gender gap in employment and also the gender gap in the daily wage rate.[20] Here, the earnings in the farm sector include wage earnings while the non-farm sector earnings include both wage earnings and profits from self-employed activities in the sector.

In Section 3.2, we claimed that women are more likely to work closer to their homes, unlike men. Table 3.1, Panel D, shows data on workplace location by gender. Here, 'Outside village' is defined as an indicator variable that equals one if an individual reports positive employment days outside the village in a given month. Similarly, 'Migration' is an indicator variable that takes a value of one for an individual who reports migrating for work in any activity in a given month. The table shows that 29% of men report working outside the village in any activity in a given month, while only 4% of women do so. Not surprisingly, the gender gap in working as a migrant is 11%. We also calculate the distance to work by measuring the distance from home to the location where the work was undertaken.[21] The unconditional (conditional on paid

[18]For an individual to be classified as being in the labor force in the NSS he/she should have engaged in 30 days of work or sought work in a year, as against the VDSA which requires working or seeking work for more than one day in a given month. The VDSA is, thus, likely to give a higher LFPR rate. Also, the NSS surveys, compared to other nationally representative datasets like India Human Development Survey, have been shown to not capture employment in livestock and animal care well which can underestimate women's work, many of whom are involved in this activity. See: IHDS report.

[19]We find a similar pattern of a much larger gender gap in employment in non-farm than the gender gap in farm employment using the 61^{th}, 64^{th}, 66^{th} and 68^{th} rounds of the NSS, as discussed later in Section 3.4.2.

[20]The gender wage gap (ln(male wage)-ln(female wage)) is much higher in the non-farm sector (72%) than in the farm sector (41%).

[21]To clarify, this does not reflect the actual distance travelled. For instance, an individual may have stayed in

employment) average distance to work, including seasonal migration for work, is over 77 (268) km for women, compared to 2179 (3776) km for men in a given month.

Rainfall

We use high spatial resolution, daily gridded (0.25 x 0.25 degree) rainfall data collected by the Indian Meteorological Department (IMD) for the last 45 years, i.e., 1971-2015. We match the latitude-longitude of each sampled village to the nearest point on the grid to generate monthly rainfall data at the village level. Following Jayachandran (2006), our measure of the rainfall shock, namely a drought, is defined to occur when the monsoon rainfall lies in the bottom two deciles of the rainfall distribution for that village over the past 45 years. Over 80% of the annual precipitation in India is received during the months of June-September (Turner and Annamalai, 2012). This is the main south-east monsoon season for India and the amount of rainfall received during this period is not only important for the kharif season (cropping season during the monsoon) but also in recharging the aquifers which are used for irrigation during the rabi season (post-monsoon cropping season).[22] Therefore, as in the literature, we define monsoon rainfall in a given agricultural year as the sum of rainfall during June-September.[23] Using this definition, Figure 3.1 shows an upward trend in the number of grids facing droughts between 1901-2017 in India. In our sample, villages received an average monsoon rainfall of 777 mm during 2010-14, 5% lower than the average over the past 45 years (Panel C, Appendix Table 3A.1). Drought-like conditions were experienced by 26% of the villages during these five years. Following the existing literature, we assign all households within a geographic region, in our case a village, the same value of the drought shock.

We validate our measure of drought by assessing its impact on agricultural output and yield for the sampled villages in the VDSA study. The detailed estimation strategy and results are discussed in Appendix 3.A.B. As expected, we find a negative effect on the production and yield of rice by 56.1% and 33.2% respectively, in a drought year. We also find that the average farm revenue of a household falls by 27.7%, although imprecisely, while profits fall significantly by

a nearby town for 10 days, which is 100 km away, and in the remaining 20 days worked in the village. The total distance to the place of work in that month for that individual will be calculated as $(10\times100 + 20\times0)$=1000 km. If an individual did not engage in any employment in a given month then this measure takes a value of zero.

[22]We classify months into agricultural seasons for the individual level analyses as follows – *kharif* (June-November), *rabi* (December-March) and *summer* (April-May).

[23]For instance, to define the drought shock for the agricultural year 2010-11, we sum up the village level rainfall for the monsoon months of June 2010-September 2011 and obtain the drought measure using the aforementioned methodology. We then assign this drought shock to the months July 2010 onwards until the onset of the next monsoon in 2011, for all households in that village.

49.5% due to drought. These results reported in Appendix Table 3A.3 confirm that our measure of drought accurately captures the shortage of water resulting from low rainfall, thus reducing agricultural productivity.[24] Lastly, we find a significant reduction in the total labor use on the farm by 24% (Appendix Table 3A.4), with labor use in upstream tasks of preparation of land and sowing affected less than downstream labor-intensive tasks like weeding and harvesting by a drought shock.[25] Labor used for weeding falls by 84.2%, as weed growth gets stunted due to low rainfall and that for harvesting falls by 50.3%.[26]

3.3.2 Empirical Strategy

Our main estimating equation is as follows:

$$y^g_{ihvmst} = \beta^g_0 + \beta^g_1 Drought_{vt} + \beta^g_2 X_{ihvt} + \delta^g Z_{hvt} + \pi^g S_{vt} + D^g_i + D^g_s + D^g_t + \epsilon^g_{ihvmst} \quad \text{(B.6)}$$

where y^g_{ihvmst} represents the labor market outcome for individual i in household h, in village v, in month m in season s and year t. A $Drought$ is an indicator variable that takes a value of one if the monsoon rainfall in the village v in year t lies in the first or second decile of the long term rainfall distribution for that village, and zero otherwise. We estimate this equation separately for each gender $g \in \{female, male\}$. Here, β^g_1 estimates the impact of drought on individuals' labor market outcomes, under the identification assumption that the drought shock is uncorrelated with other shocks to labor demand or supply in a village in a given year. Given the unanticipated nature of rainfall and our interest in looking at the reduced form impacts of the drought in equilibrium on labor market outcomes, this assumption holds. Our main coefficient of interest is $\beta^{female}_1 - \beta^{male}_1$, which estimates the impact of drought on women relative to men for a given labor market outcome.

In our empirical specification, we transform the continuous dependent variables, i.e., work-days and earnings, using the Inverse Hyperbolic Sine (IHS) transformation to take into account zero values for labor use and earnings in a given month for an individual. The advantage of this transformation is that it is defined at zero and the regression coefficients (β^g_1) can be interpreted as a percentage change in the outcome variable due to a drought.[27] On the other hand, for

[24] Refer to notes of Appendix Table 3A.3 on measurement of outcome variables.

[25] Weeding and harvesting are the most labor-intensive operations utilising 107.4 and 219.34 labor hours, respectively, on average in a season in a year.

[26] We find similar results when we consider per-acre labor usage hours as the dependent variable.

[27] The transformation is given by $log(y) = log(y+(y^2+1)^{1/2})$ (Burbidge et al., 1988). While this transformation estimates the effect in percent terms with little error for variables with values greater than 10, it underestimates the

binary outcome variables which capture employment outcomes on the extensive margin, β_1^g is interpreted as percentage point change due to a drought.

X_{ihvt} is a vector of individual-level controls that may vary over time, e.g. marital status. Z_{hvt} are time-varying household controls that can affect individual employment choices – family composition (number of children, number of female and male members in the working-age group), the distance of the house from the nearby market (to capture distance to nearest urban areas where non-farm jobs are available) and average education level (in years) of the household adults. Additionally, we interact the initial asset index and the real value of durables in the first year the household was surveyed with a linear time trend to take into account differential labor use trends over time by the wealth of the household. We also control for the upper two deciles of monsoon rainfall in a village in a given year (S_{vt}) since a priori it is not clear whether high rainfall reflects a positive or negative productivity shock as higher than usual rainfall can also create a flood-like situation that reduces farm productivity.[28]

We include a range of fixed effects in our specification —D_i^g represents individual fixed effect that controls for unobserved, time-invariant, individual-level factors that may affect labor allocation by men and women in a household, D_s^g represents season fixed effect and D_t^g is an year fixed effect.[29] The standard errors are clustered at the village-season level since the drought measure is defined at the village level and shocks within the village for the same season are likely to be correlated.

3.4 Results

3.4.1 Main results

We report the estimated effect of drought on labor market outcomes using equation (B.6) in Table 3.2. Columns (1)-(2) report the results for overall participation in the labor market, while

effect if the variable takes values below 10 (Bellemare and Wichman, 2020). Since the average workdays in our sample are below this threshold, we multiply them by 10 to reduce the error. We also estimate specifications by taking logs and adding a very small positive value to zero and continue to find similar results in percentage terms. Thus, our results are not sensitive to the IHS transformation in particular.

[28]Existing papers, using district-level data, show that rainfall in the upper deciles can have a positive productivity effect over the entire district (Jayachandran, 2006; Emerick, 2018). In our village-level data, we find that the upper deciles of rainfall do not have any positive impact on farm productivity.

[29]We choose to carry out the regression analysis with agricultural season fixed effects even when our data varies at the monthly level. This is to ensure that we accurately capture the seasonal nature of rural labor markets and to keep the analysis consistent with the seasonal agricultural demand. Our results remain unchanged even with month fixed effects.

columns (3)-(4) and columns (5)-(6) report the estimates for its constituents 'Employed' and 'Unemployed', respectively, by gender. Panel A shows the estimates on the extensive margin while Panel B captures the intensive margin impacts as defined in Table 3A.2. In each panel, the first row reports the coefficient on 'Drought'. The second row ('Difference') captures the gender differential between women and men in the effect of drought on the outcome variables.[30] The mean of the binary dependent variable is reported in the last row of Panel A.

The results indicate that droughts can have opposing effects on the labor market outcomes of women and men. While the labor force participation of women is affected insignificantly, men increase their participation by 0.6 percentage points (pp) (Panel A, columns (1)-(2)) in response to a drought. Consequently, the gender differential in labor force participation increases by 1.2 pp or 5.2% (at the mean gender difference) when a drought occurs.[31] The overall effect on labor market participation hides another heterogeneity by gender - women are 1.2 pp less likely to be employed (column (3)) but 1.6 pp more likely to seek work (column (5)) when a drought occurs while there is no significant effect on men's employment or unemployment. Thus, women are 1.7 pp less likely to be employed and 3.2 pp more likely to look for work, relative to men (row 'Difference'). This implies a fall (rise) in women's employment (unemployment) by 7.1% (80%) relative to that of men.

We find similar effects of drought on the intensive margin of labor market outcomes in Panel B of Table 3.2. There is a negative but insignificant change in the total days participated in the labor market for women (column (1)). Women's employed workdays fall by 15.3% (column (3)) while the number of days they look for work increase by 14.4% (column (5)). Men's total workdays in labor market, as well as employed workdays, increase insignificantly (column (2) and (4)) but their days seeking work reduce by 15% (column (6)). As a result, employed workdays fall significantly more for women by 19%, while there is a significant increase in involuntary unemployment days for women by 29.4%, relative to men.

Next, Table 3.3 reports the effect of drought on dis-aggregated employment, i.e., by the nature of engagement in different types of work. We use three categories for the type of work – farm (paid or family) in columns (1)-(6), livestock (columns (7)-(8)) and non-farm (columns (9)-(10)), as defined in Table 3A.2. Again, Table 3.3, Panel A shows the estimates on the extensive margin

[30] We run a fully interacted specification using the pooled sample of men and women to estimate the coefficients and standard errors for this difference. To elaborate, we interact the drought measure, as well as all other controls, with a female dummy variable that equals one for women and zero for men.

[31] The relative effect of drought on LFPR for women versus men in percentage is calculated by dividing the gender differential in employment due to drought, in this case given by 1.2 pp, by the gender differential in mean LFPR rates in the row 'Mean Y' in Panel A of Table 3.2, given by (92 pp - 69 pp) = 23 pp. This equals 5.2%.

while Panel B reports it for the intensive margin. Columns (1)-(2), show that there is a negative, though insignificant, effect of drought on total farm employment. However, columns (3)-(6) show that there is heterogeneity across paid and family farm. Women's participation in paid farm work is unaffected (column (3)), but men's falls by 1.6 pp or 13.3% at the mean (column (4)) during a drought. There is no significant effect on participation in family farm for either gender (columns (5)-(6)). Consequently, women's paid farm participation rises by 2.1 pp during drought years, relative to men's. On the other hand, family livestock care work by women falls by 1.6 pp (3.8% at the mean) in column (7), while men are 2.1 pp (4.5% of the mean) more likely to participate in non-farm sector work (column (10)). Thus, women's participation in both livestock and non-farm sectors falls by 1.9 pp and 1.8 pp, respectively, relative to men.

We observe similar effects on the intensive margin in Panel B of Table 3.3. Women's workdays, relative to men's, on paid farm increase by 15.3% (columns (3)-(4)) but contract in livestock care by 18.9% (columns (7)-(8)) and 20.1% (columns (9)-(10)) in the non-farm sector, respectively. Thus, the overall fall in women's relative employment on both the extensive and intensive margins, reported in Table 3.2 (columns (3)-(4)), is driven by relatively lower participation by women in livestock and non-farm sectors during a drought. The VDSA data also captures average hours worked per day in the paid farm and non-farm sectors by an individual in a given month, but not for family farm and family livestock work. In Appendix 3.A.B, we examine the effect of drought on total hours worked in paid farm and non-farm work categories. We find that women's hours, relative to men's, in paid farm increase by 13.1% but contract in the non-farm sector by 18.7% (Appendix Table 3A.5). Thus, our previous findings for monthly workdays continue to hold for monthly hours of work as well.

To summarise, we find a significant gender differential in the responses of women and men to drought in paid farm and non-farm work. Men substitute away from paid farm work (13.3%) and take up non-farm work (4.5%) to cope with the productivity shock due to droughts. The workdays by men in paid farm fall (13.7%) while those in paid non-farm work increase (22.5%). In contrast, women are less likely to diversify their workdays away from the farm to the non-farm sector when a drought occurs. We find a decline in women's livestock workdays by 21% but no effect on women's farm and non-farm workdays. The gendered effects lead to a 15.3% gain in farm workdays while the non-farm and livestock workdays decline by 20.1% and 18.9%, respectively, for women relative to men, during a drought.[32] These findings suggest that the

[32]We also check for multiple hypothesis testing using the standard FDR Q method given the multiple outcomes in our analysis (Anderson, 2008; Benjamini and Yekutieli, 2001). Our main result of diversification to non-farm

lower returns from farming during drought years push men away from farm work and towards non-farm jobs while women continue to work on the farm with reduced intensity.[33]

Clearly, the above results show that women's employment, on the extensive as well as the intensive margin, falls more relative to that of men due to droughts. In Table 3.4, columns (1)-(4) report the effect of drought on monthly earnings, columns (5)-(8) on monthly earnings conditional on positive workdays, and columns (9)-(12) on daily wage rates (monthly earnings/workdays) for the farm and non-farm sectors and by gender.

The results indicate an insignificant change in the monthly earnings of women in both farm (column (1)) and non-farm (column (3)) work due to a drought. But men's farm earnings fall significantly by 18.5% (column 2) while their non-farm earnings increase by 17.5%. Consequently, although farm earnings fall less for women by 18.9%, their non-farm earnings fall more by 18.6%, relative to that of men. The relative changes in earnings for both genders are consistent with the results for workdays discussed above. However, summing up the paid farm earnings and non-farm earnings, there is no significant difference in earnings during a drought for either men or women (results omitted for brevity). This shows that men's diversification from the farm to the non-farm sector enables households to cope with a drought shock in terms of recuperating lost earnings from hired work in the farm sector.[34]

Next, we analyse earnings conditional on working in columns (5)-(8) in Table 3.4, to gauge how earnings for those who choose to be engaged in a given type of work change due to droughts. We find that women's earnings fall by 38.1% (column (5)) while there is an insignificant change for men (column (6)) in the event of a drought for paid farm earnings.[35] Conversely, the non-farm conditional earnings are negative but insignificant (10%, column (7)) for women and fall significantly for men by 9% (column (8)) during a drought. As a result, conditional farm earnings fall more for women by 34.7% relative to men while there is no gender differential in the conditional non-farm earnings.

Lastly, we look at the effects of drought on the marginal productivity of labor in different

work by men on extensive as well as intensive margins during a drought continues to remain significant.

[33]Although we do not find any effects of the upper two deciles of rainfall on farm profits and revenue, excess rainfall also leads to an increase in non-farm employment for men relative to women (Emerick, 2018).

[34]It is however important to note that a large part of income loss is due to lower profits on the family farm, thus non-farm diversification may not be able to provide full cushioning to the household income losses from all types of work —own farm, paid farm and livestock. In fact, our findings show that total household incomes (paid farm earnings, livestock earnings, non-farm earnings, and profits from farms) fall by around 8% in a drought year.

[35]The negative effect of droughts on conditional paid farm earnings of women with an insignificant effect on their overall monthly paid farm earnings can be explained by women's higher participation and increased workdays, albeit insignificant, in the farm sector (Table 3.3, column (3)).

types of work. We examine how daily wage rates by gender respond to drought shock in columns (9)-(12), again conditional on working. We find that farm daily wage rates fall more for women (11.4%) while there is no significant effect for men (columns (9)-(10)).[36] On the other hand, non-farm wage rates fall by 7-8% for both women and men but the fall is significant only for men with an insignificant gender differential (columns (11)-(12)). Hence, the results suggest that conditional on working women experience a relatively larger fall in farm wage rates – consistent with the existing evidence that wage rate responses to productivity shocks are likely to be larger in the farm sector when labor has fewer options to diversify to the non-farm sector (Jayachandran, 2006).

To sum up, our results show that women's days in employment fall relative to men's by 19% when a drought strikes. This is due to no change in their total days of work in the farm or the non-farm sectors, albeit a fall in their workdays in the livestock sector. However, men's days of work in the non-farm sector increase during a drought. Thus, women continue to work in the farm sector during a drought, but with reduced intensity of work, and consequently a lower relative daily wage rate, while men move to non-farm sector employment. In congruence with our main results, we not only find that men residing in villages with higher rainfall variance allocate more workdays to the non-farm sector, but also observe a larger gender gap in non-farm sector employment in these areas.[37] Thus, both the short-term and possibly the longer-term effects of climate change can be deleterious for women in terms of exacerbating gender gaps in non-farm employment.

3.4.2 Robustness checks

Balanced sample

As mentioned previously, our individual-level data set is an unbalanced panel since new household members join and others leave the sample over time. This may bias our estimates above due to sample selection. Therefore, as a robustness check, we restrict the sample to a balanced panel of individuals for whom data are available for all twelve months of each year from 2010-14. This comprises 73.7% of our original sample. The regression results for labor allocation across

[36] We also examine the effect of drought on hourly wage rate in the farm sector since we have earlier seen a reduction in hours worked by women in response to drought. We again find that there is a 9.4% decline in hourly wage rates for women in the farm sector in a drought while there is no effect for men.

[37] Here, rainfall variance is measured by the observed variability in monsoon rainfall. A village is classified as high variability when its coefficient of variation of monsoon rainfall (=Standard Deviation/Mean) is above the median of the distribution across villages.

sectors remain unchanged and are reported in Panel A of Table 3.5. We find that women continue to work in the farm sector while men move to the non-farm sector when a drought hits. This leads to an overall greater decline in the days employed for women relative to men by 19.6% (columns (1)-(2)) in a drought year. The previous findings for earnings and wage rates also continue to hold for this sample.

Unconditional sample

Although the VDSA survey records monthly employment information for all household members including migrants, for some individuals the employment information is missing for some months. This can be due to reporting errors or if a member permanently leaves the household for marriage, work or expires. These missing data may not only bias our individual estimates but also the gender differences if either gender is systematically more likely to suffer from misreporting. Therefore, as a robustness check, we consider a full sample of all individuals aged 15 and above who were recorded in the annual household survey at the beginning of the year *unconditional* on being observed in a given month. For the months for which employment data are missing we assign a value of zero to overall workdays and workdays by sector. This increases our original sample by 4.2%. The regression results are reported in Panel B of Table 3.5 and remain similar to our main findings above.

Village-specific trends

Throughout our analysis we account for changes in outcome variables over time through year fixed effects. However, our results may be confounded by village-specific annual trends in employment and other socio-economic factors. We, therefore, account for village specific linear trends as an additional control in our specification. Our conclusions do not change as shown by the results in Panel C of Table 3.5.

Alternative measure of drought shock and other controls

We first check if our results on labor market effects of a contemporaneous drought shock are robust to the inclusion of lagged rainfall shock measures and temperature. In Appendix Table 3A.6, columns (1)-(4), we introduce one year lag, in addition to the contemporaneous value, for both our drought and excess rainfall shock in the main specification. This allows us to separate the contemporaneous effect of the shock from the lagged effect. Our results for the contemporaneous drought shock remain similar. In columns (5)-(8), we introduce controls for temperature and its square to check if the drought effects remain significant even after controlling for temperature fluctuations.[38] We measure temperature as the Harmful Degree Days (HDDs) during the monsoon season defined as the sum of the deviations of daily maximum temperature above the median of its long-run village-level monthly maximum temperature over the monsoon period. Our findings on the effects of drought on paid farm and non-farm work remain unchanged.

Second, the literature lacks consensus on a consistent measure of drought. We, therefore, consider two alternative measures of a drought shock in Appendix Table 3A.7. Following the standard agricultural production literature, columns (1)-(4) use a continuous measure of the shock - negative of the standard deviation of monsoon rainfall from its long-run average. Again, we find that men are more likely to move to the non-farm sector by 10% for every one standard deviation increase in the negative rainfall shock. We find no significant effect of the drought measure on female or male paid farm employment. Our second drought measure in columns (5)-(8) uses temperature to capture the negative productivity shock. It defines drought as the Harmful Degree Days (HDDs) of temperature over the monsoon season (without controlling for drought resulting from low precipitation). Our results using this alternative definition of drought remain similar, with an additional HDD reducing the paid farm workdays and increasing non-farm workdays of men equally by 0.3%. We find no significant effect for women either for the farm or non-farm work. Consequently, paid farm (non-farm) workdays increase (fall) more for women by 0.3%, relative to men for an additional HDD.

Nationally representative data

The VDSA panel data allow us to obtain the most consistent estimates of drought impacts on labor allocation across sectors by accounting for individual-level unobserved heterogeneity. However, the VDSA data are collected for just 30 villages, which raises concerns about sample selectivity. We, therefore, use the National Sample Survey (NSS), nationally representative data, which provides employment information for a repeated cross-section of households and individuals in each round, to validate our main findings. We use recent rounds of data that most closely overlap with our period of analyses above – 2004-05, 2007-08, 2009-10, and 2011-12. We restrict the analyses to rural areas and consider individuals aged 15 years and above. Here,

[38] While, temperature and drought shock may be correlated (0.29, p<0.01), the variation in temperature over half a decade is not large for our time period of study.

farm and non-farm workdays are defined as the sum of the number of days spent in farm and non-farm activities respectively, in the last reference week by an individual.[39] We again take an IHS transformation of workdays to account for zero days of work.[40] Our drought measure is now defined at the district level since this is the smallest administrative unit that can be mapped to an individual in the NSS dataset. The drought indicator takes a value of one when the monsoon rainfall lies in the bottom two deciles of the long-run average for that district in a given year and zero otherwise.[41]

The results from this nationwide analysis, reported in the Appendix Table 3A.8, are consistent with the findings using the VDSA data and show that farm to non-farm diversification in the event of a drought is significant only for men. There is a significant reduction in farm workdays due to drought for both women (12.1%) and men (8.3%), with no significant gender differential. On the other hand, non-farm workdays increase only for men (9.7%) during a drought. This generates a significant gender differential, whereby women's work in the non-farm sector decreases relative to men's by 10% due to a drought. Hence, our main findings from the VDSA data continue to hold using an alternative pan-India dataset.

3.5 Mechanisms

The above results on the effect of drought on employment as well as wages by gender show that women are less likely to diversify from the farm to the non-farm sector when a negative productivity shock hits the farm sector. Hence, women are more likely to bear the burden of staying in risky employment, which is also less productive and hence pays a lower wage rate, during a drought. What factors explain this gender-differentiated substitution of labor towards non-farm sector employment in response to the weather shock? We take advantage of the rich VDSA data to analyse workplace location and migration decisions by gender, as well as the heterogeneity in our estimates by demographic characteristics that are often determinants of women's mobility.

[39] 2011-12 is the last available NSS survey round. We do not use the more recent Periodic Labor Force Surveys (PFLS) which replaced the NSS in 2017 as they do not report the operation codes required to create the farm and non-farm work classification. Also, the measurement of hours of work is different across the NSS and the PLFS surveys. The NSS sampling ensures that households are surveyed every quarter in each district to ensure representativeness over the agricultural year.

[40] Before undertaking this transformation, we multiply them by 10 to reduce the error as discussed in Section 3.3.2.

[41] We construct our measure of district-level rainfall by taking an average of monthly rainfall over the grids of IMD data that overlap with the district, weighted by the area of the overlap with each such grid.

3.5.1 Workplace location and seasonal migration

Seasonal migration can be an important coping mechanism during adverse shocks in the agriculture sector. A reduction in farm incomes can also reduce demand for non-farm work within a village. In such a scenario, migration to or travelling to nearby locations may become necessary to find (non-farm) jobs. However, as mentioned previously in Section 3.3, women are more likely to be restricted in terms of their mobility and may engage in work closer to their homes (Table 3.1, Panel D). Consequently, women may be less likely to explore work opportunities beyond their vicinity even in the event of a negative productivity shock that lowers employment opportunities within the village.

We test this hypothesis by estimating the impact of drought on workplace location and migration (unconditional on employment status) using equation (B.6). The results are reported in Table 3.6. In columns (1)-(2), the dependent variable takes a value of one if an individual reports working within the village in a given month in any activity and zero otherwise, while columns (3)-(4) report results when the dependent variable is 'Outside village'. The analysis shows no significant effect of drought on the probability of working within the village for both sexes, though the sign of the coefficient for women is positive. However, in relative terms, women are 1.4 pp or 35% more likely to work within the village in comparison to men during a drought (columns (1)-(2)). On the other hand, men are 1.8 pp or 7.2% more likely to work outside the village relative to women when faced with a drought shock (columns (3)-(4)).

In Table 3.6, columns (5)-(6), we report the results when the dependent variable is an indicator variable for 'Migration' by an individual in a given month, as defined earlier. The probability of migration during a drought increases by 0.8 pp for men (column (6)) or 6.2% of the mean. On the other hand, we find a zero likelihood that women work outside the village (column (3)) or migrate (column (5)) in response to drought. The reported effects of drought on the distance to work for women and men further validate these results.[42] We find an insignificant change in distance to work for women (column (7)), while for men the distance to work increases by 19.9% (column (8)) when a drought occurs. Therefore, not only are men more likely to migrate during a drought but they are also likely to travel a longer distance on average in search of work. Women's mobility is, however, constrained.[43]

[42]Information on distance travelled is available conditional on moving out of the village for work. We assign a value of zero to the distance travelled for those who report working inside the village or who do not work. We then take the IHS transformation of the distance variable to account for zeroes in the dependent variable.

[43]We also find that male migration for work is relatively higher than that of females in villages that experience greater variability in monsoon rainfall, suggesting a longer-term impact on the structure of the labor market due to

3.5.2 Social costs

Do social costs emanating from gender norms influence women's labor mobility and thereby lead to the observed gender-differentiated labor responses? The gendered norms around home production responsibility and sexual 'purity' are likely to reduce women's mobility as observed above and conceptualized in Section 3.2. Women who have young children and are married are more likely to be responsible for both domestic chores and care-giving duties towards children and elderly, relative to other women. Concerns around sexual purity, besides home-production responsibilities, are often higher for adolescent women of marriageable age or married women in the reproductive age, relative to older women.

Table 3.7, columns (1)-(2) report the heterogeneous effect of drought on non-farm workdays by indicator variables for the young (15-39 year olds), currently married (columns (3)-(4)) and parents to children below the age of 10 years in columns (5)-(6), across gender. Row (A) reports the effect for the base category (i.e., $Z = 0$) while row (B) tests for heterogeneity by the characteristic (Z). The row 'Difference (A)' reports the gender differential between women and men for the base category (i.e., $Z = 0$) while the row named 'Difference ((A)+(B))' does so for the main category (i.e., $Z = 1$). As expected, we find that social constraints translate into significantly lower non-farm days for younger women and women with young children, relative to older women and those without kids, by 14.6% and 21.4% respectively, when faced with a drought shock (row (B), columns (1) and (5)). We find no significant heterogeneity in female response by marital status.

Our estimates indicate that younger women, married women and those with kids are unable to increase their non-farm days when faced with a drought shock, unlike men who belong to the same groups, as indicated by the significant negative gender differential for each of these categories (row 'Difference ((A)+(B))'). Although unmarried women and those without young children also work fewer days in the non-farm sector relative to men in the same categories, the negative effect is larger for married women and women having young children. These results highlight the possible role of norms around women's home production responsibilities being higher for those with children and concerns around purity being higher for young women.

We also examine the heterogeneity in the probability of migration due to a drought along these characteristics in Table 3.8. The coefficients in row 'Difference ((A)+(B))' are all more negative than those in row 'Difference (A)', and statistically significant, showing limited migration by

extreme weather events.

women, relative to men, in these demographic categories during a drought. This reinforces our earlier finding that the prevalence of social norms places a disproportionate burden of home production on women along with concerns around their sexual purity, hindering their mobility and access to alternative sources of work in the event of farm production shocks.

Our proposed mechanism is further validated by the existing evidence that provision of employment close to home helps women cope with negative income shocks disproportionately more than men (Afridi et al., 2022a). Indeed, we find that the National Rural Employment Guarantee Scheme (NREGS), a rights-based employment program that provides work within the village and also mandates 33% of rural works for women helps weather the negative labor market effects due to droughts on women. VDSA survey records data on the number of workdays spent by an individual under NREGS each month only for 13 villages out of 30 villages. Appendix Table 3A.9 shows that NREGS workdays increase insignificantly by 12.7% (column (1)) for women and by 1.1% for men (column (2)) during a drought, rendering the gender difference positive but insignificant. These estimates are imprecise given the data constraints in VDSA for capturing NREGS workdays. Hence, we also use administrative data available from the NREGS public data portal to examine the role of such public works as employment insurance against droughts at the Gram Panchayat (GP) level.[44] Restricting our analysis to the sample of eight states of the VDSA data for the period 2011-14, we find that women benefit differentially more from this scheme by 3.5% (Appendix Table 3A.9).

There are two alternative explanations of women's limited diversification to the non-farm sector during droughts – lack of non-farm sector skills and safety concerns. We do not find evidence in support of either mechanism. In Table 3.9, we report the effect of drought on workdays by type of non-farm sector jobs in the VDSA data. We find no gender differential in the skilled non-farm workdays. On the contrary, there is a 10.6% increase in the unskilled non-farm workdays of men relative to women during a drought (columns (1)-(2)). In Appendix Table 3A.10, we report the heterogeneous effects of a drought on non-farm workdays using NSS data (2004-05, 2007-08, 2009-10 and 2011-12) across high versus low women related crime districts (excluding crimes like domestic violence) classified using National Crime Records Bureau data for 2004. Clearly, the magnitude of the gender difference in the effect of drought

[44] For administrative purposes, India is divided into 6862 sub-districts. Each sub-district contains about 30 Gram Panchayats (GPs) which are the primary unit of local governance. Each GP comprises approximately 4-5 villages. The data on the annual (April-March) workdays generated for women and men are available at the GP level from NREGA Public Data Portal from 2011 onwards. We construct our measure of drought using rainfall at the centroid of the sub-district. Each GP is then assigned the drought measure of its respective sub-district.

on non-farm workdays does not vary across the high and low crime districts. In fact, we find a significant gender difference in the effect of drought on non-farm workdays in both types of districts (row 'Difference ((A)+(B))').

It is theoretically possible that our findings can be explained by differential changes in demand in the farm/non-farm sector across gender when droughts occur. However, this is difficult to test since we observe only equilibrium employment outcomes. Additionally, it is less likely that demand would vary differentially by age, marital status and parenthood, between women and men.[45] Overall, the above findings provide plausible evidence that social norms around home production and sexual purity restrict female mobility, thus constraining their ability to diversify to the non-farm sector when negative productivity shocks occur in the farm sector.

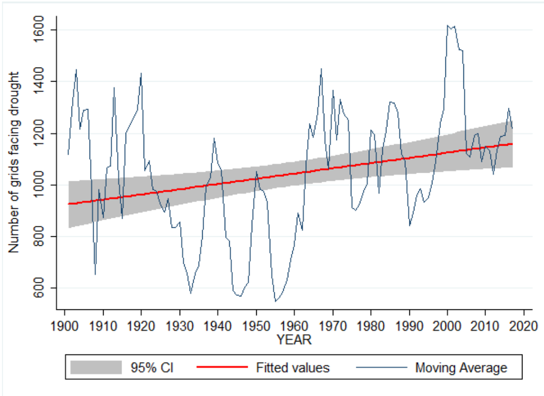
3.6 Conclusion

Rural households dependent on the farm sector increasingly face the risk of negative productivity shocks like droughts, especially in rain-fed agriculture systems of developing countries, due to climate change. We find that the impact of extreme weather events resulting from adverse climatic changes may not be gender-neutral, especially in developing countries with social norms that constrain women's labor mobility. Our results show that women are more likely to face employment losses as they are unable to cope with these negative effects by diversifying to the less risky, higher return, non-farm work. Women are less likely to migrate and thus are unable to benefit from alternative sources of employment. While the observed choices may be optimal for households, our results show that as climate shocks become more persistent they can exacerbate existing gender inequities in the labor market and beyond. Thus, gender-neutral shocks can have gendered impacts.

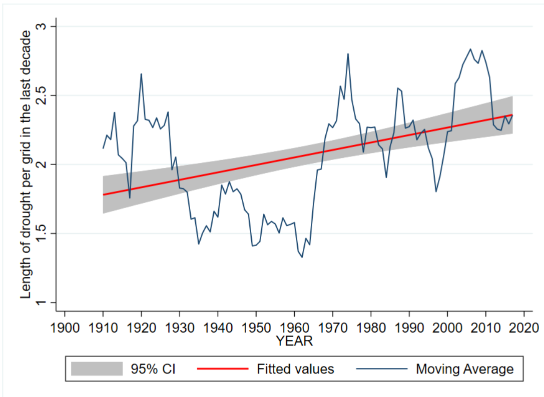
[45] Lower bargaining power of women within the household can also constrain their mobility and hence access to non-farm work outside the village. To the extent that social norms determine the relative bargaining power of spouses within a household (Jayachandran, 2015), our findings can be explained by these norms.

3.7 Figures and Tables

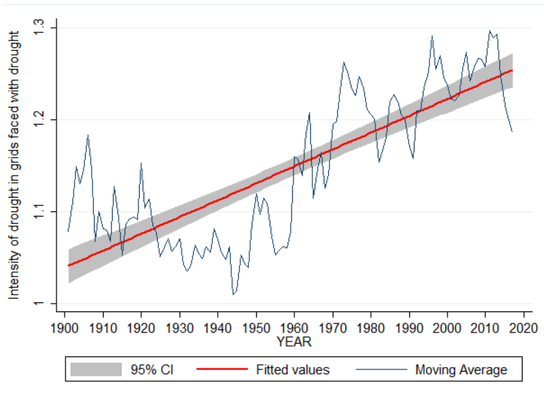
Figure 3.1: Frequency, Duration and Intensity of Droughts in India (1901-2017)



(a) Frequency



(b) Duration



(c) Intensity

Source: IMD data (1901-2017)
Note: A drought occurs when the monsoon rainfall in a grid lies in the bottom two deciles of the long-run distribution (1901-2017). Figure (a) plots the five-year moving average of the *Frequency of droughts*. Figure (b) plots the duration as measured by the *Length of drought* – the average number of drought years in each grid experienced in the preceding decade. Figure (c) plots the five-year moving average of *Intensity of drought* – the standard deviation of monsoon rainfall in a grid from its long-run average during the drought year.

Table 3.1: Summary Statistics: Individual-month level, by gender

	Female			Male		
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.
Panel A: Labor market participation per month						
Labor force	134721	0.69	0.46	145214	0.92	0.26
Employed	134721	0.68	0.47	145214	0.92	0.27
Unemployed	134721	0.06	0.24	145214	0.10	0.30
Paid farm	134721	0.18	0.38	145214	0.12	0.33
Family farm	134721	0.36	0.48	145214	0.50	0.50
Family livestock	134721	0.42	0.49	145214	0.44	0.50
Non-farm	134721	0.12	0.33	145214	0.47	0.50
Panel B: Workdays per month						
Labor force days	134721	12.82	13.15	145214	22.65	13.85
Employed days	134721	12.23	12.65	145214	21.65	13.36
Unemployed days	134721	0.58	3.08	145214	1.00	3.98
Paid farm days	134721	2.39	5.77	145214	1.74	5.27
Family farm days	134721	2.45	4.41	145214	4.40	6.35
Family livestock days	134721	4.88	9.12	145214	5.26	9.19
Non-farm days	134721	2.51	7.33	145214	10.26	12.11
Unskilled	134721	0.41	3.06	145214	2.54	7.08
Skilled	134721	0.63	3.77	145214	2.82	7.65
Business/Salaried	134721	1.23	5.45	145214	4.67	10.10
Panel C: Real wage earnings per month (Rs.)						
Paid farm earnings	134721	37.10	98.16	145214	41.89	182.24
Non-farm earnings	134721	56.46	263.89	145214	448.76	1012.95
Paid farm earnings (Conditional)	23692	210.95	134.61	17712	343.37	410.80
Non-farm earnings (Conditional)	16692	447.03	601.96	67554	956.24	1304.41
Farm wage rates	23692	15.56	6.34	17712	23.34	16.96
Non-farm wage rates	16692	21.14	23.41	67554	43.41	76.68
Panel D: Workplace in a month						
Within village	134721	0.25	0.43	145214	0.29	0.45
Outside Village	134721	0.04	0.20	145214	0.29	0.46
Migration	134721	0.02	0.12	145214	0.13	0.33
Distance to work (kms.)	134721	77.10	1170.99	145214	2179.13	9156.47
Distance to work excluding migrants (kms.)	132649	5.63	135.89	126736	105.49	1351.05
Panel E: Non-farm workdays by demographic groups						
Young	76652	2.60	7.47	83376	12.14	12.39
Older	58069	2.40	7.13	61838	7.73	11.24
Married	102630	2.48	7.20	101175	10.42	12.03
Unmarried	32091	2.63	7.72	44039	9.87	12.30
Parent	36431	2.19	6.69	36237	12.91	12.07
Non-Parent	98290	2.63	7.55	108977	9.38	12.00

Source: VDSA micro level data.
Note: Earnings and wage rates are deflated using the Consumer Price Index for Agricultural laborers (CPIAL) and show values as of the base year 1986-87 of the index.

Table 3.2: Effect of Drought on Labor Market Outcomes

	Labor Force		Employed		Unemployed	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Extensive Margin (Participation)						
Drought	-0.006	0.006*	-0.012*	0.005	0.016*	-0.016
	(0.007)	(0.003)	(0.006)	(0.003)	(0.008)	(0.010)
Difference	-0.012**		-0.017***		0.032***	
	(0.006)		(0.005)		(0.009)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.654	0.569	0.651	0.560	0.295	0.348
Mean Y	0.69	0.92	0.68	0.92	0.06	0.1
Panel B: Intensive Margin (Workdays)						
Drought	-0.081	0.026	-0.153**	0.036	0.144*	-0.150*
	(0.082)	(0.047)	(0.073)	(0.048)	(0.079)	(0.089)
Difference	-0.107*		-0.190***		0.294***	
	(0.059)		(0.055)		(0.082)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.679	0.642	0.675	0.628	0.330	0.369
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: In Panel A, the dependent variables are indicator variables for the labor force, employed and unemployed status of an individual in a given month in columns (1)-(2), (3)-(4) and (5)-(6), respectively. In the corresponding columns in Panel B, the dependent variables are an IHS transformation of the labor force, employed and unemployed days of an individual in a given month, respectively. Table 3A.2 shows the definition of the variables. In each panel, the first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean Y' denotes the mean value of the dependent variable in Panel A. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.3: Effect of Drought on Employment, by Type of Work

	Farm						Livestock		Non-farm	
	Total		Paid		Family		Family			
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Extensive Margin (Participation)										
Drought	-0.009	-0.003	0.005	-0.016***	-0.011	-0.002	-0.016*	0.003	0.003	0.021***
	(0.010)	(0.008)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)	(0.006)	(0.005)
Difference	-0.005		0.021***		-0.009		-0.019**		-0.018***	
	(0.008)		(0.007)		(0.008)		(0.009)		(0.007)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.603	0.582	0.611	0.519	0.596	0.598	0.681	0.669	0.612	0.690
Mean Y	0.45	0.54	0.18	0.12	0.36	0.5	0.42	0.44	0.12	0.47
Panel B: Intensive Margin (Workdays)										
Drought	-0.052	-0.068	0.016	-0.137**	-0.053	-0.039	-0.210***	-0.020	0.024	0.225***
	(0.092)	(0.079)	(0.051)	(0.058)	(0.086)	(0.073)	(0.080)	(0.074)	(0.066)	(0.061)
Difference	0.016		0.153**		-0.015		-0.189**		-0.201***	
	(0.076)		(0.065)		(0.077)		(0.085)		(0.071)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.615	0.613	0.623	0.527	0.605	0.632	0.678	0.687	0.629	0.704
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: In Panel A, the dependent variables in columns (1)-(2), (3)-(4), (5)-(6), (7)-(8) and (9)-(10) are indicator variables for employment in farm, paid farm, family farm, family livestock and non-farm, respectively. In the corresponding columns in Panel B, the dependent variables are an IHS transformation of workdays spent in farm, paid farm, family farm, family livestock and non-farm, respectively. The dependent variable in column (1)-(2) of Panel A ('Total Farm') is an indicator variable that equals one when an individual works either in the paid farm or family farm work in a given month. Similarly, in Panel B it corresponds to an IHS transformation of the sum of workdays spent in paid farm and family farm work. Other dependent variables are defined in Table 3A.2. In each panel, the first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean Y' denotes the mean value of the dependent variable in Panel A. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 3.4: Effect of Drought on Real Wage Earnings

	Monthly Earnings				Monthly Earnings (Conditional)				Daily Wage Rate			
	Paid Farm		Non-farm		Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Drought	0.005	-0.185***	-0.010	0.175**	-0.381***	-0.034	-0.100	-0.090**	-0.114***	0.036	-0.073	-0.081***
	(0.056)	(0.064)	(0.072)	(0.075)	(0.079)	(0.106)	(0.092)	(0.040)	(0.037)	(0.059)	(0.048)	(0.029)
Difference	0.189**		-0.186**		-0.347***		-0.010		-0.151**		0.008	
	(0.073)		(0.085)		(0.119)		(0.083)		(0.065)		(0.051)	
Observations	134,709	145,202	134,709	145,202	23,647	17,627	16,645	67,809	23,647	17,627	16,645	67,809
R-squared	0.622	0.526	0.642	0.723	0.425	0.498	0.725	0.728	0.619	0.628	0.777	0.781
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the monthly earnings from paid activities, monthly earnings (conditional on working in a given sector) and average daily wage rates of an individual in a given sector of work (paid farm or non-farm) in a given month in columns (1)-(4), (5)-(8) and (9)-(12), respectively. Table 3A.2 shows the definition of the variables. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. In columns (5)-(6), we only include the interaction of wealth in the first year of the survey with annual trends and drop the interaction with assets because of singularity of the variance matrix. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 3.5: Effect of Drought on Workdays: Robustness

	Employed		Farm				Livestock		Non-farm	
			Paid		Family		Family			
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Balanced Sample										
Drought	-0.200**	-0.004	-0.015	-0.155**	-0.035	-0.029	-0.257***	-0.053	0.029	0.178***
	(0.084)	(0.047)	(0.056)	(0.070)	(0.094)	(0.072)	(0.096)	(0.085)	(0.077)	(0.061)
Difference	-0.196***		0.140*		-0.007		-0.205**		-0.149*	
	(0.066)		(0.075)		(0.080)		(0.097)		(0.078)	
Observations	97,025	109,295	97,025	109,295	97,025	109,295	97,025	109,295	97,025	109,295
R-squared	0.644	0.525	0.627	0.522	0.603	0.636	0.669	0.693	0.627	0.700
Panel B: Unconditional Sample										
Drought	-0.107	0.028	0.020	-0.141**	-0.038	-0.053	-0.170**	-0.033	0.033	0.234***
	(0.076)	(0.053)	(0.050)	(0.056)	(0.083)	(0.073)	(0.080)	(0.075)	(0.064)	(0.057)
Difference	-0.135**		0.160**		0.015		-0.137		-0.202***	
	(0.059)		(0.063)		(0.075)		(0.089)		(0.065)	
Observations	140,184	151,608	140,184	151,608	140,184	151,608	140,184	151,608	140,184	151,608
R-squared	0.652	0.592	0.615	0.520	0.601	0.627	0.662	0.670	0.607	0.683
Panel C: Village-specific annual trends										
Drought	-0.129*	0.021	-0.017	-0.067	-0.056	-0.005	-0.123*	-0.107*	0.002	0.136**
	(0.074)	(0.038)	(0.046)	(0.048)	(0.081)	(0.077)	(0.070)	(0.056)	(0.057)	(0.054)
Difference	-0.149***		0.051		-0.051		-0.015		-0.134**	
	(0.056)		(0.065)		(0.051)		(0.062)		(0.064)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.680	0.633	0.628	0.533	0.615	0.639	0.685	0.696	0.632	0.708
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of workdays spent in overall employment, paid farm, family farm, livestock and non-farm work by an individual in a given month in columns (1)-(2), (3)-(4), (5)-(6), (7)-(8), and (9)-(10), respectively. Table 3A.2 defines all the outcome variables. Panel A reports the results for the balanced sample of individuals, Panel B reports the results for the sample of all individuals aged 15 and above who were recorded in the annual household survey at the beginning of the year *unconditional* on being observed in a given month and Panel C reports the results with village-specific annual trends. In each panel, the first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Panel C, in addition to the above controls, allows for village-specific annual trends. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.6: Effect of Drought on Place of Work

	Within Village		Outside Village		Migration		Distance to Work	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought	0.004	-0.010	-0.000	0.017***	0.001	0.008**	-0.012	0.199***
	(0.006)	(0.006)	(0.003)	(0.006)	(0.001)	(0.003)	(0.028)	(0.074)
Difference	0.014**		-0.018***		-0.007**		-0.211***	
	(0.007)		(0.006)		(0.003)		(0.071)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.659	0.603	0.588	0.675	0.643	0.721	0.606	0.701
Mean Y	0.25	0.29	0.04	0.29	0.02	0.13	77.10	2179.13
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables take a value of one for an individual in a given month if the individual spends at least one day engaged in work within the village, work outside the village and work related seasonal migration in that month, in columns (1)-(2), (3)-(4) and (5)-(6), respectively. In columns (7)-(8), the dependent variable is an IHS transformation of the distance (km.) to the workplace for an individual in a given month - defined as the sum of the distance for all work days in a month with zero distance given to work within village and no work. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean Y' denotes the mean value of the dependent variable. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.7: Heterogeneous Effect of Drought on Non-farm Workdays

Characteristic (Z):	Young		Married		Parent	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Drought	0.108	0.218***	-0.009	0.175	0.080	0.229***
	(0.070)	(0.059)	(0.081)	(0.116)	(0.070)	(0.065)
(B) Z x Drought	-0.146**	0.014	0.043	0.070	-0.214**	-0.020
	(0.059)	(0.088)	(0.079)	(0.120)	(0.085)	(0.107)
Difference (A)	-0.109		-0.184		-0.149	
	[0.14]		[0.07]		[0.04]	
Difference ((A)+(B))	-0.27		-0.212		-0.343	
	[0]		[0.02]		[0.01]	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.629	0.704	0.629	0.704	0.629	0.704
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variable is an IHS transformation of workdays spent in non-farm work by an individual in a given month.*Young* is an indicator variable for individuals in the 15-39 age category in a given year; *Married* indicates individuals who report marital status as currently married in a given year; *Parent* indicates individuals with children below 10 years of age in a given year. For our main categories ($Z = 1$), these characteristics equal one and zero for the base categories ($Z = 0$). The first row (A) reports the regression coefficients for drought for the base categories while the second row named (B) reports the heterogeneity in the effect by the characteristics. The third row (Difference (A)) reports the gender differential for the base category while the fourth row (Difference (A)+(B)) reports it for the main category. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses and p-values are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.8: Heterogeneous Effect of Drought on Migration

Characteristic (Z):	Young		Married		Parent	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Drought	0.000	0.005*	0.001	-0.000	0.001	0.004
	(0.001)	(0.003)	(0.002)	(0.007)	(0.001)	(0.004)
(B) Z x Drought	0.001	0.005	-0.001	0.011	-0.002	0.018**
	(0.002)	(0.006)	(0.002)	(0.009)	(0.003)	(0.008)
Difference (A)	-0.005		0.002		-0.002	
	[0.09]		[0.83]		[0.49]	
Difference ((A)+(B))	-0.009		-0.011		-0.023	
	[0.09]		[0.01]		[0]	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.643	0.721	0.643	0.721	0.643	0.721
Mean Y (Z=0)	0.01	0.05	0.02	0.17	0.01	0.12
Mean Y (Z=1)	0.02	0.18	0.01	0.11	0.02	0.15
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.

Note: The dependent variable takes a value of one for an individual who spends one or more days engaged in seasonal migration for work in that month and zero otherwise.*Young* is an indicator variable for individuals in the 15-39 age category in a given year; *Married* indicates individuals who report marital status as currently married in a given year; *Parent* indicates individuals with children below 10 years of age in a given year. For our main categories ($Z = 1$), these characteristics equal one and zero for the base categories ($Z = 0$). The first row (A) reports the regression coefficients for drought for the base categories while the second row named (B) reports the heterogeneity in the effect by the characteristics. The third row (Difference (A)) reports the gender differential for the base category while the fourth row (Difference (A)+(B)) reports it for the main category. 'Mean Y (Z=0)' and 'Mean Y (Z=1)' denote the mean values of the dependent variable for the base and the main category, respectively. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses and p-values are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.9: Effect of Drought on Non-farm Workdays: Skilled vs Unskilled

	Unskilled		Skilled		Business/Salaried	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	0.002	0.106**	0.029	0.061	-0.038	0.039
	(0.017)	(0.047)	(0.030)	(0.044)	(0.040)	(0.036)
Difference	-0.104**		-0.032		-0.078	
	(0.044)		(0.050)		(0.048)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.448	0.585	0.558	0.644	0.654	0.711
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of workdays spent in different types of non-farm work. Column (1)-(2) report the results for unskilled workdays, column (3)-(4) report the results for skilled workdays and column (5)-(6) report the results for business/salaried workdays. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

3.A Appendices

3.A.A Conceptual Framework (Proof)

The profit maximizing equilibrium labor demand with the farm production function as specified in Eq. (B.3) is given by:

$$L_a = \left(\frac{\theta B^{\epsilon} - \theta\epsilon B^{\epsilon}}{w_a}\right)^{1/\epsilon} \tag{3A.7}$$

The utility maximization exercise in Section 3.2 gives the following first order conditions for interior solutions:

$$u_a - \Psi = 0 \tag{3A.8}$$

$$u_n - p\Psi = 0 \tag{3A.9}$$

$$u_{l_a} - \Psi w_a = 0 \tag{3A.10}$$

$$u_{l_n} - v_{l_n} - \Psi w_n = 0 \tag{3A.11}$$

Total differentiation of equations (3A.8) through (3A.11) and (B.2) yields:

$$\begin{pmatrix} u_{11} & u_{12} & u_{13} & u_{13} & -1 \\ u_{12} & u_{22} & u_{23} & u_{23} & -p \\ u_{13} & u_{23} & u_{33} & u_{33} & -w_a \\ u_{13} & u_{23} & u_{33} & u_{33} - v_{11} & -w_n \\ -1 & -p & -w_a & -w_n & 0 \end{pmatrix} \begin{pmatrix} \mathrm{dc}_a \\ \mathrm{dc}_n \\ -\mathrm{dl}_a \\ -\mathrm{dl}_n \\ \mathrm{d}\psi \end{pmatrix} = \begin{pmatrix} 0 \\ \mathrm{dp}\psi \\ \mathrm{dw}_a\psi \\ \mathrm{dw}_n\psi \\ \mathrm{dp}c_n - \mathrm{dw}_a l_a - \mathrm{dw}_n l_n \end{pmatrix} \tag{3A.12}$$

Solving the above systems of equations (using Cramer's rule) we obtain the following labor supply responses of women and men to a drought shock (D) for farm (a) and non-farm (n) work:

$$\frac{dl_{af}}{dD} = \left(\frac{dl_{af}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{R+S}{H+Z}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{3A.13}$$

$$\frac{dl_{am}}{dD} = \left(\frac{dl_{am}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{R}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{3A.14}$$

$$\frac{dl_{nf}}{dD} = \left(\frac{dl_{nf}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{J}{H+Z}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{3A.15}$$

$$\frac{dl_{nm}}{dD} = \left(\frac{dl_{nm}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{J}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{3A.16}$$

Under the assumption that a drought is a negative productivity shock in the agricultural sector i.e., $\left(-\frac{dw_a}{dD}\right) > 0$, the sign of the above derivatives i.e., response of the labor supply to drought, will depend on the terms in the first set of parentheses. These terms are a collection of double derivatives and their expressions are given below:

$$
\begin{aligned}
J &= w_n(l_1(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
&+ \psi(-pu_{11}u_{23} + pu_{12}u_{13} + u_{12}u_{23} - u_{13}u_{22})) \\
&+ w_a(\psi(-pu_{11}u_{23} + pu_{12}u_{13} + w_n(u_{11}u_{22} - {u_{12}}^2) + u_{12}u_{23} - u_{13}u_{22}) \\
&- l_1(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22})) \\
&+ \psi(u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) - (u_{23} - pu_{13})^2) \\
H &= (w_a - w_n)^2(u_{11}({u_{23}}^2 - u_{22}u_{33}) + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
Z &= v_{11}(u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) + 2w_a(-pu_{11}u_{23} + pu_{12}u_{13} + u_{12}u_{23} - u_{13}u_{22}) \\
&- (u_{23} - pu_{13})^2 + w_a^2(u_{11}u_{22} - {u_{12}}^2)) \\
R &= l_1(w_a - w_n)(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
&+ \psi(-u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) + 2w_n(pu_{11}u_{23} - pu_{12}u_{13} - u_{12}u_{23} + u_{13}u_{22}) \\
&+ (u_{23} - pu_{13})^2 + w_n^2({u_{12}}^2 - u_{11}u_{22})) \\
S &= v_{11}(l_1(-pu_{11}u_{23} + pu_{12}u_{13} + w_a(u_{11}u_{22} - {u_{12}}^2) + u_{12}u_{23} - u_{13}u_{22}) \\
&+ \psi(p^2u_{11} - 2pu_{12} + u_{22}))
\end{aligned}
\tag{3A.17}
$$

Using equation (3A.16), the conditions under which men diversify to the non-farm sector due to a drought are as follows:

$$\frac{dl_{nm}}{dD} \geq 0 \begin{cases} H > 0 \\ H, J < 0 \end{cases}$$

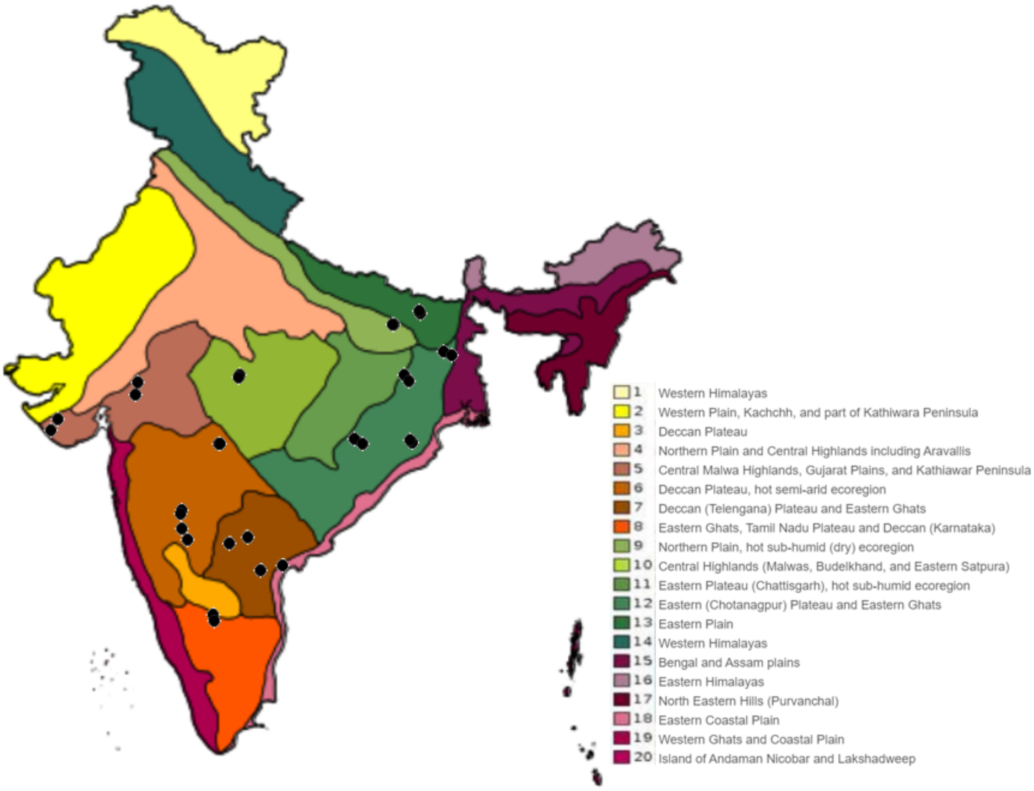
Using equations (3A.15) and (3A.16), the conditions for a negative gender differential in non-farm employment due to a drought i.e., women diversify less to the non-farm sector relative to men due to a drought, are given by:

$$\frac{dl_{nf}}{dD} - \frac{dl_{nm}}{dD} \leq 0 \begin{cases} H > 0, 0 \leq Z \\ H < 0, J < 0, |H| < Z or Z < 0 \end{cases}$$

And the converse holds otherwise.

3.A.B Additional Analyses, Tables and Figures

Figure 3A.1: Sampled Villages



Source: VDSA (`http://vdsa.icrisat.ac.in/vdsa-map/vdsa-location-map.html`).
Note: The black dots mark the 30 villages in the VDSA data. The colors represent different agro-ecological zones as classified by the National Bureau of Soil Survey & Land Use Planning (NBSS & LUP).

Table 3A.1: Summary Statistics

Variable	Obs	Mean	S.D.	Definition
Panel A: Individual Characteristics				
Age	5931	35.05	17.11	years
Education	5930	7.43	4.94	years of education completed
Female	5931	0.49	0.50	=1 if female, 0 otherwise
Married	5931	0.65	0.48	=1 if currently married, 0 otherwise
Parent	5931	0.25	0.43	=1 if parent of child below the age of 10 years, 0 otherwise
Panel B: Household Characteristics				
Children	1367	1.56	1.52	number of children <15 years of age
Working-age women	1367	1.72	0.99	number of women in 15-65 age group
Working-age men	1367	1.88	1.12	number of men in 15-65 age group
Average education	1367	5.25	3.31	mean years of education (members >14 years)
Market distance	1367	11.70	7.07	distance from nearest market town (kms.)
Wealth	1367	11641.87	28109.10	value of durable assets (Rs.)
Asset index	1367	-0.20	0.87	PCA of assets
Panel C: Village Characteristics				
Current rainfall	30	776.68	283.32	monsoon rainfall (mm) (2010-14)
Historical rainfall	30	812.64	309.64	monsoon rainfall (mm) (1970-2014)
Drought	30	0.26	0.23	bottom two deciles of the long-run average monsoon rainfall (2010-14)
Flood	30	0.17	0.17	top two deciles of the long-run average monsoon rainfall (2010-14)

Source: VDSA micro level data.
Note: The variables in Panel A and Panel B are at the individual and household level, respectively. The values for wealth and assets index are constructed using data reported by households in the first year it was surveyed. Wealth includes the sum of values of all durable assets owned by the household. The asset index is constructed using the principal components analysis (PCA) on the households' ownership of different assets (bathroom, cooking gas, drinking-water well, electricity, residential house, tap water connection and toilet). Panel C is unique at village level.

Table 3A.2: Summary Statistics (Individual-month level)

Variable	N	Mean	S.D.	Definition
Panel A: Labor market participation per month (Extensive margin)				
Labor force	279935	0.81	0.39	=1 if employed or sought work, 0 otherwise
Employed	279935	0.80	0.40	=1 if worked for a positive number of days, 0 otherwise
Unemployed	279935	0.08	0.27	=1 if sought work for a positive number of days, 0 otherwise
Paid farm	279935	0.15	0.36	=1 if worked for a positive number of days in paid farm work, 0 otherwise
Family farm	279935	0.43	0.49	=1 if worked for a positive number of days in family farm work, 0 otherwise
Family livestock	279935	0.43	0.50	=1 if worked for a positive number of days on family livestock, 0 otherwise
Non-farm	279935	0.30	0.46	=1 if worked for a positive number of days in non-farm work, 0 otherwise
Panel B: Workdays per month (Intensive margin)				
Labor force days	279935	17.92	14.38	number of days worked or seeking work
Employed days	279935	17.12	13.85	number of days worked (farm plus non-farm)
Unemployed days	279935	0.80	3.58	number of days spent seeking work
Paid farm days	279935	2.05	5.52	number of days worked in paid farm
Family farm days	279935	3.46	5.59	number of days worked in family farm
Family livestock days	279935	5.08	9.16	number of days worked on family livestock
Non-farm days	279935	6.53	10.81	number of days worked in non-farm
Panel C: Real wage earnings per month (Rs.)				
Paid farm earnings	279935	39.58	147.89	real earnings from paid farm work, 0 if unemployed or not working in paid farm
Non-farm earnings	279935	259.96	777.30	real earnings from non-farm work, 0 if unemployed or not working in non-farm
Paid-farm earnings(Conditional)	41401	267.60	297.71	real earnings from farm work if working in paid farm work in that month, missing otherwise
Non-farm earnings(Conditional)	84215	855.71	1215.81	real earnings from non-farm work if working in non-farm work in that month, missing otherwise
Farm wage rate	41401	19.32	12.84	earnings per work day in paid farm in a month
Non-farm wage rate	84215	39.01	70.04	earnings per work day in non-farm in a month

Source: VDSA micro level data.

Note: The sample includes all individuals aged 15 and above in the years 2010-2014. The first column reports the outcome variables used in the analyses for employment and earnings and the last column reports their definitions. Panel A and B show the summary statistics for the full sample for all individuals at a monthly frequency for 2010-2014. In Panel C, the first two rows use the full sample while the following rows show the summary statistics conditional on working in the sector (resulting in the observations being smaller for these rows). Earnings and wage rates are deflated using Consumer Price Index for Agricultural laborers (CPIAL) with the base year 1986-87.

Validity of Drought Measure:

We confirm that our measure of drought accurately captures the scarcity of water resulting from low rainfall in Table 3A.3 below. The farm productivity is negatively affected as indicated by the 56.1% (column (1)) fall in production and 33.2% (column (2)) reduction in yield of rice in a drought year. The average farm revenue of a household falls by 27.7% (column (3)), although imprecise, while profits fall significantly by 49.5% due to drought (column (4)).

Additionally, Table 3A.4 reports a reduction in the total labor use on-farm by 24% (column (1)). Since the preparation of land is the first operation to be performed at the start of the agriculture season, tasks included in land preparation are completed even before the onset of the monsoon. Hence, labor use in upstream tasks of preparation of land and sowing is likely to be affected less by a drought shock than downstream labor-intensive tasks like weeding and harvesting. Indeed, we find no significant effect of our measure of drought on labor use in land preparation and sowing (columns (2) and (3)), though the sign is negative and the magnitude is around 4-5%. The requirement for weeding and harvesting labor falls during a drought by 84.2% (column (4)) and 50.3% (column (5)), respectively, as yields plummet and additionally, weed growth gets stunted due to low rainfall. We find similar results when we consider per-acre labor usage hours as the dependent variable.

Table 3A.3: Effect of Drought on Farm Output and Productivity

	Rice		All Crops	
	Output	Yield	Revenue	Profit
	(1)	(2)	(3)	(4)
Drought	-0.561**	-0.332*	-0.277	-0.495***
	(0.256)	(0.181)	(0.191)	(0.171)
Observations	114	114	11,606	11,606
R-squared	0.865	0.720	0.383	0.438
Mean Y	35067.19	4133.66	8404.209	-12540.13
Village FE	✓	✓		
Year FE	✓	✓	✓	✓
Household FE			✓	✓
Season FE			✓	✓
Other controls			✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the village-level output and yield of rice in columns (1) and (2) and household-level revenue and profit in columns (3) and (4), respectively. The coefficient on *drought* can thus be interpreted as the percentage change in the dependent variable. 'Output' is the total production of rice by all households in a village during the *Kharif* season in a year. 'Yield' is the rice output divided by the total area cultivated under rice in that village in a year. Therefore, columns (1)-(2) are unique at the village-season-year level and restrict to the *Kharif* season only as rice is primarily a *Kharif* crop. 'Revenue' is the total production value of the crops harvested by a cultivating household in a given agricultural season and year. It is obtained by multiplying the price of each crop cultivated by the total production of that crop by the household. 'Profit' is the difference between revenue and cost of inputs including hired labor, but not family labor, in a given agricultural season and year. Both these dependent variables are in real terms (deflated with CPIAL with base as 1986-87) and defined at the household-season-year level. 'Mean Y' denotes the mean value of the dependent variable (without IHS transformation). The specifications in columns (1) and (2) control for village and year fixed effects while that in columns (3) and (4) controls for household, season, year fixed effects and other controls. Other controls include household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3A.4: Effect of Drought on Hours of Farm Labor Use by Operation

	Total (1)	Preparation (2)	Sowing (3)	Weeding (4)	Harvesting (5)
Drought	-0.240***	-0.050	-0.043	-0.842***	-0.503*
	(0.082)	(0.156)	(0.177)	(0.305)	(0.284)
Observations	8,657	8,657	8,657	8,657	8,657
R-squared	0.569	0.484	0.559	0.519	0.380
Mean Y	655.1	50.91	26.08	107.4	219.34
Household FE	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the hours of farm labor usage by a cultivating household in a given season and year. Column (1) reports the effect of drought on total labor use while columns (2)-(5) report it by operation for preparation of land, sowing, weeding and harvesting, respectively. The coefficient on drought can thus be interpreted as the percentage change in the dependent variable. 'Mean Y' denotes the mean value of the dependent variable (without IHS transformation). All specifications control for household, season, year fixed effects and other controls. Other controls include household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Effect of Drought on Intensive Margin of Work: Table 3A.5 shows the results for total hours worked in a month as the dependent variable in equation (B.6), for only paid farm and non-farm work. Similar to the results for extensive margin and workdays, we find that women's hours, relative to men's, in paid farm increase by 13.1% (columns (3)-(4)) but contract in non-farm by 18.7% (columns (5)-(6)).

Table 3A.5: Effect of Drought on Hours of Work

	Paid Farm + Non-farm		Paid Farm		Non-farm	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	0.004	0.084	0.017	-0.113**	0.012	0.198***
	(0.064)	(0.074)	(0.049)	(0.055)	(0.058)	(0.061)
Difference	-0.080		0.131**		-0.187***	
	(0.071)		(0.061)		(0.068)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.692	0.705	0.623	0.523	0.626	0.708
Mean Y	32.75	93.27	17.53	13.01	15.23	80.26
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the hours of work spent in total paid (paid farm+non-farm) activities, paid farm activities and non-farm activities by an individual in a given month in columns (1)-(2), (3)-(4) and (5)-(6), respectively. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean' denotes the mean value of dependent variable (without IHS transformation). All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3A.6: Effect of Drought on Workdays: Robustness (Additional Specifications)

	Lagged shocks				Temperature and its square			
	Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Drought	0.011	-0.179***	0.048	0.211***	0.006	-0.139*	-0.006	0.230***
	(0.058)	(0.066)	(0.081)	(0.073)	(0.066)	(0.076)	(0.088)	(0.071)
Lag Drought	0.100	0.011	-0.008	-0.141*				
	(0.064)	(0.066)	(0.053)	(0.079)				
$Temp$					0.002	0.006	0.005	-0.005
					(0.003)	(0.004)	(0.004)	(0.003)
$Temp^2$					-0.000	-0.000**	-0.000	0.000*
					(0.000)	(0.000)	(0.000)	(0.000)
Difference	0.190***		-0.163*		0.145*		-0.237***	
	(0.069)		(0.093)		(0.078)		(0.082)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.624	0.527	0.629	0.704	0.623	0.527	0.629	0.704
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the paid farm and non-farm workdays of an individual in a given month. All the specification in columns (1)-(8) are the same as our main specification and additionally control for a one year lag of drought and flood (columns (1)-(4)), and quadratic form of temperature shock in column (9)-(12). The temperature shock measures Harmful Degree Days (HDDs) during the monsoon season defined as the sum of the deviations of daily maximum temperature above the median of its long-run village-level monthly maximum temperature over the monsoon period. The first row reports the regression coefficients for drought while the second row reports the estimates for one year lagged drought shock followed by temperature and temperature square and the last row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3A.7: Effect of Drought on Workdays: Robustness (Alternative Measures of Drought)

	Drought Measure 1				Drought Measure 2			
	Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Drought	0.002	0.049	-0.023	0.101**	-0.000	-0.003***	-0.000	0.003**
	(0.040)	(0.040)	(0.034)	(0.048)	(0.001)	(0.001)	(0.001)	(0.001)
Difference	-0.047		-0.124***		0.003***		-0.003**	
	(0.047)		(0.042)		(0.001)		(0.001)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.623	0.526	0.629	0.704	0.623	0.527	0.629	0.704
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the paid farm and non-farm workdays of an individual in a given month. In columns (1)-(4), the drought measure ('Measure 1') is the negative of the standard deviation of monsoon rainfall from its long-run average. The drought measure ('Measure 2') in columns (5)-(8) is the Harmful Degree Days (HDDs) during the monsoon season defined as the sum of the deviations of daily maximum temperature above the median of its long-run village-level monthly maximum temperature over the monsoon period. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3A.8: Effect of Drought on Workdays: Robustness (NSS data)

	Farm		Non-farm	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Drought	-0.121***	-0.083**	-0.003	0.097***
	(0.041)	(0.036)	(0.022)	(0.030)
Difference (Drought)	-0.038		-0.100***	
	(0.046)		(0.030)	
Observations	430,905	434,566	430,905	434,566
R-squared	0.186	0.147	0.079	0.150
Mean Y	1.09	2.46	0.53	2.4
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Other controls	✓	✓	✓	✓

Source: National Sample Survey, Employment and Unemployment rounds (2004-05, 2007-08, 2009-10 and 2011-12).
Note: The sample includes all individuals aged 15 and above in rural regions of India for the NSS rounds between (2005-14), i.e., 2004-05, 2007-08, 2009-10 and 2011-12. The dependent variables are an IHS transformation of the farm and non-farm workdays of an individual in the preceding seven days from the date of the survey in a given year. Here drought is a district level measure. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean' denotes the mean value of workdays in each specification. All specifications control for district and year fixed effects and other controls. Other controls include individual characteristics (age, square of age, education and marital status), household characteristics (religion and social group) and district level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at district level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3A.9: Effect of Drought on NREGS days

	VDSA		NREGS Portal	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Drought	0.127	0.011	0.370***	0.335***
	(0.157)	(0.276)	(0.074)	(0.073)
Difference	0.115		0.035*	
	(0.243)		(0.019)	
Observations	5,195	5,641	405,105	405,105
R-squared	0.640	0.521	0.700	0.697
Mean Y	3.6	3.39	2774.52	3394.71
Individual FE	✓	✓		
Year FE	✓	✓	✓	✓
GP FE			✓	✓
Other controls	✓	✓	✓	✓

Source: VDSA micro level data and NREGS Public Data Portal (2011-2014).
Note: The dependent variables are an IHS transformation of the NREGS workdays reported in the VDSA data by an individual in a given year in columns (1) and (2) while in columns (3) and (4) it is the IHS transformation of total NREGS person-days generated in a Gram Panchayat (GP) in a year. The drought measure in columns (1)-(2) is at village level while in columns (3)-(4) is at sub-district level. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean' denotes the mean value of NREGS days in a given specification (dependent variable without IHS transformation). The specification in columns (1)-(2) control for the individual, year fixed effects and other controls. In these columns, other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at the village level are reported in parentheses. The specification in columns (3)-(4) control for the GP, year fixed effects. In these columns, other controls include GP level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at sub-district level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3A.10: Heterogeneous Effect of Drought on Non-farm Workdays: Role of Women's Safety

District characteristic (Z):	Crime Measure 1		Crime Measure 2	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
(A) Drought	-0.028	0.066	-0.031	0.066
	(0.026)	(0.043)	(0.026)	(0.043)
(B) Z x Drought	0.059	0.057	0.063	0.058
	(0.043)	(0.059)	(0.043)	(0.059)
Difference (A)	-0.094		-0.097	
	[0.03]		[0.02]	
Difference ((A)+(B))	-0.092		-0.092	
	[0.03]		[0.03]	
Observations	415,987	419,512	415,987	419,512
R-squared	0.078	0.149	0.078	0.149
Mean (Z=0)	0.47	2.37	0.46	2.36
Mean (Z=1)	0.58	2.42	0.59	2.42
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Other controls	✓	✓	✓	✓

Source: NSS (2004-05, 2007-08, 2009-10 and 2011-12) and National Crime Records Bureau (NCRB) (2004).
Note: The dependent variable is an IHS transformation of the non-farm workdays of an individual in the preceding seven days from the date of the survey in a given year. The drought measure is constructed at the district level. Women-related crimes is the total number of crimes (rape, kidnapping and abduction of women, assault on women with intent to outrage her modesty, insult to modesty of women) reported in each district in 2004. 'Crime Measure 1' takes a value of one for districts with above median women-related crimes (per female) and zero otherwise. 'Crime Measure 2' takes a value of one for districts with above median women-related crimes (per person) and zero otherwise. For our main categories ($Z = 1$), these characteristics take a value of one and a value of zero for the base categories ($Z = 0$). The first row (A) reports the regression coefficients for drought for the base category while the second row named (B) reports the heterogeneity by the characteristic. The third row (Difference (A)) reports the gender differential for the base category while the fourth row (Difference (A)+(B)) reports it for the main category. 'Mean (Z=0)' and 'Mean (Z=1)' denote the mean values of the dependent variable (without IHS transformation) for the base and the main category, respectively. The sample includes all individuals aged 15 and above in rural regions of India in the NSS data. Since NCRB data for some districts of NSS are not available in 2004, the number of observations here are lower than the main NSS analysis. All specifications control for district, year fixed effects and other controls. Other controls include individual characteristics (age, square of age, education and marital status), household characteristics (religion and social group) and district level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at district level are reported in parentheses and p-values are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1).

Chapter 4

Employment Guaranteed? Social Protection During a Pandemic[1]

4.1 Introduction

The Covid-19 pandemic is an unprecedented health and economic shock to the world economy. Most major economies are in recession and unemployment has peaked, demanding a response from policymakers that ensures sustainable economic recovery. Social safety nets, a somewhat neglected policy tool - including employment guarantees, unemployment insurance, Universal Basic Income (UBI) - are once again being debated.[2] Furthermore, ongoing research on the pandemic suggests that economic impacts differ across demographic groups (Desai et al., 2021; Afridi et al., 2021; Lee et al., 2021; Deshpande, 2020; Platt and Warwick, 2020), but there is limited evidence on both the role played by social safety nets in stemming labor market disruptions as well as their impacts across population groups, which may well vary depending on the design of programs. For instance, unlike a UBI that would not distinguish between working and dependent populations, employment guarantees provide support during labor market shocks

[1] This paper is a joint work with Farzana Afridi (ISI-Delhi) and Kanika Mahajan (Ashoka University), and is published in Oxford Open Economics. Refer to Afridi et al. (2022a).

[2] An ILO report discusses the various schemes implemented in the Asia-Pacific region during this pandemic. Rees-Jones et al. (2020) review various social safety nets in Europe and the United States.

to the workforce, potentially impacting productivity and bolstering demand by enhancing incomes (Devereux, 2002).[3] In addition, the benefits of employment guarantee schemes may differ by worker characteristics, depending on the nature of work offered and skills required.

We measure the impact of the pandemic induced shutdown in one of the worst affected economies due to the crisis - India. We first assess the overall effects of the nationwide shutdown during April-August 2020 on individuals' employment status and its dynamic impact by phases - Phase I of stringent mobility restrictions (April-May), with gradual easing in Phase II (June-July) and full relaxation in Phase III (August). We then examine the role of the nation-wide Mahatma Gandhi National Rural Employment Guarantee Act (MG-NREGA), the world's largest employment guarantee program initiated in 2006 and bolstered following the pandemic, in cushioning job losses overall and as the stringency of the restrictions eased during April-August 2020. To address the endogeneity of employment generated under the program during the pandemic, we use historical data on employment generation under MG-NREGA in a district over five years, from 2014-18, to measure the capacity of the state to provide social protection under the scheme during this crisis.

Using nation-wide, individual-level panel data with over a million observations and employing an approach akin to a difference-in-differences (DID) estimation strategy we compare changes in general employment status between 2019 and 2020, across January-March (control months) and April-August (treated months). We find that individual-level employment fell precipitously during the lockdown phase of April-May 2020 relative to January-March 2020, compared to the change over the same period in 2019. Employment showed a V-shaped recovery post the lockdown (April-May) with easing of mobility restrictions (June-July) but tapered off and continued to remain below the pre-pandemic level as the economy reopened (August).

The DID estimates indicate that historical program capacity to provide work under MG-NREGA stemmed employment loss in rural areas and women therein, during this period. We find that an increase in state capacity to provide MG-NREGA work by one day per rural inhabitant (approximately moving a district from 50^{th} to 95^{th} percentile of the MG-NREGA historical state capacity distribution) in a month reduced job losses in rural areas post the nationwide lockdown by 3.1 percentage points (pp) overall or 7% over the baseline employment rate. Rural women's employment increased relatively, by 8.6 pp or 74%, suggesting that not only were employment

[3] Pissarides (1992) shows that a short negative employment shock can lengthen unemployment duration leading to potential loss of skills and further "thinning" of the labor market as the human capital of the labor force erodes. Hence there can be long-term implications of even short episodes of economic downturn.

losses for women stemmed, but women who were previously not in the labor force may also have entered the labor market during the crisis in high state capacity districts. On the other hand, the effect on rural men's employment while positive was small and insignificant. Overall, high historical state capacity to provide MG-NREGA cushioned job losses more in rural areas in Phase III (August 2020) - by 4.8 pp or by 10.8%, and 13.1 pp or almost 100% for rural women. These findings are robust to individual-level heterogeneity, district and occupation-specific trends.

To the best of our knowledge, this is the first paper to evaluate the effectiveness of a pre-existing public employment guarantee on nation-wide employment during the Covid-19 pandemic. Studies suggest buffering (but perhaps small) effects of unemployment insurance during Covid-19 crisis on employment and income in the context of the U.S. (Altonji et al. (2020), East and Simon (2020), Moffitt and Ziliak (2020), Farrell et al. (2020)) but an assessment of labor market impacts of social safety nets are largely absent for developing countries. Our findings are validated by smaller, bespoke studies conducted during the pandemic. Using survey data from urban India Dhingra and Machin (2020) find that workers who had an employer-provided private job guarantee of a minimum number of days of work in a year before the pandemic, were 5 pp more likely to remain employed during the crisis. A choice experiment with the same sample suggests that low-wage workers were willing to work at 25% lower wage if their job could be guaranteed; women were significantly more likely to prefer a guaranteed job relative to men. While previous research has highlighted the role of MG-NREGA on women's workforce participation due to its mandated reservation of jobs for women, equal pay and access to work close to home (Afridi et al., 2016), our results are also consistent with the role of women's jobs as insurance (Sabarwal et al., 2011) and the counter-cyclicality of women's labor force participation in developing countries (e.g. during 1986-2006 recessions in Asia and Latin America (Bhalotra and Umana-Aponte, 2010)). Indeed, we find that MG-NREGA disproportionately benefited married women, women belonging to households with young children and less educated women during the crisis - markers of lower mobility and skills - and irrespective of their pre-crisis employment status.

Our findings have important policy implications. First, we show that employment guarantees can play a role in shielding job losses and aiding recovery from a negative economic shock. Second, the results highlight the relevance of the design of the employment guarantees in contributing towards their effectiveness. While rural areas and women - the less skilled and less mobile - benefited disproportionately from the low-wage, unskilled employment under MG-

NREGA, such social protection eluded urban areas. Thus, the nature of work and required skills can determine relative benefits by demographic groups. Finally, our research contributes to the emerging literature on the relevance of state capacity in the development process (Muralidharan et al., 2016) by indicating that state capacity to utilise public funds might be a critical determinant of governments' ability to respond quickly to economic crises.

The remainder of the paper is organised as follows. Section 4.2 discusses the time of the crisis in India and the job guarantee program. We provide details of the data in Section 4.3. The methodology and results are in Section 4.4 and Section 4.5, respectively. Section 4.6 concludes.

4.2 Background

4.2.1 Timeline

The Indian government ordered a stringent national shutdown to deal with the COVID-19 pandemic, from 24 March 2020 until April 14, which was later extended to May 30 (Phase I). In fact, India imposed one of the strictest lockdowns, restricting all economic activity except those deemed essential (Balajee et al., 2020), with just 500 reported and confirmed COVID cases at the time of the lockdown announcement. The phased reopening was initiated on June 8. This was followed by a gradual easing of restrictions on mobility in June and a further easing in night curfew and domestic air travel from July (Phase II). From August 1, Phase III of 'unlockdown' with the removal of night curfew saw further relaxations of restrictions on economic activity and mobility.[4]

As a consequence of the shutdown, the impact on economic activity across the country was catastrophic and the country entered a recession. India's GDP contracted by 23.9% during April-June and 7.5% in the second quarter (July-September) of the 2020-21 fiscal year as opposed to 4.2% growth in the GDP in 2019-20.[5] The unemployment rate peaked at 18.5% in the first quarter and started to taper-off from the second quarter onwards (7.5% in both July-September and October-December quarters).[6]

[4]See: Coronavirus India timeline: Tracking crucial moments of Covid-19 pandemic in the country, October 1, 2020, The Indian Express.

[5]See: India GDP Q2 Data: India's GDP contracts 7.5% in Q2, enters technical recession, November 27, 2020, The Indian Express.

[6]See: Unemployment Rate in India, CMIE

4.2.2 MG-NREGA

The Mahatma Gandhi National Rural Employment Guarantee Act (MG-NREGA) mandates the provision of 100 days of manual work on publicly funded projects (e.g. rural infrastructures such as irrigation canals and roads) to rural households in India. The Act envisions a rights-based approach - rural adults can demand work at a mandated minimum wage. The program was initially implemented in the country's poorest 200 districts in February 2006, with 130 additional districts added in the next stage (2007) and national coverage thereafter (2008). In 2018, the Act provided employment to almost 76 million individuals at an annual expenditure of more than Rs. 60,000 crores (or USD 9 billion), making it one of the most ambitious employment generation programs in the world. The Act also mandates reservation of 1/3rd of jobs in each MG-NREGA project for women.

Post the national shutdown on March 24, 2020, the provision of employment under the program also came to a halt. On April 15, 2020, however, the Government of India ordered activities related to the MG-NREGA to resume. It also increased allocation to the program's budget by Rs 40,000 crore. Consequently, the program generated 2.02 billion person-days of work until September 2020, compared with 1.88 billion for the entire fiscal year of 2019-20. Figure 4.1a plots the district level average person-days of work (number of people working per day multiplied by the number of days of work obtained) per rural inhabitant generated under the scheme for every month in 2020 and 2019.[7] It shows that the average person-days generated were similar in 2019 and 2020 for January-March but there was a sudden plunge in April 2020 (due to the shutdown) relative to the 2019 level. Thereafter, the average number of person-days generated in May-June 2020 saw a sharp spike, which again fell in July-August 2020, the peak agriculture season, but remained slightly higher in 2020 than in 2019 even during August. Furthermore, the gender allocation of person-days under MG-NREGA did not change from the pre-crisis period. The proportion of monthly person-days of work received by women between April-December 2020 (post-shutdown) (48.45%) was comparable to the pre-pandemic period during April 2019 to March 2020 (48.75%).[8]

Research indicates that MG-NREGA implementation has been uneven across districts of India

[7] The data for person-days is from the MG-NREGA Public Data portal: `https://nregarep2.nic.in/netnrega/dynamic2/DynamicReport_new4.aspx` and that for rural inhabitants is taken from Census 2011.

[8] We divide the cumulative person-days generated by gender (unfortunately, this information is not available at a monthly frequency, unlike the total person-days generated) by the number of months for which we have data to arrive at the average monthly person-days by gender.

(Shah and Mohanty, 2010; Dreze and Oldiges, 2009), and program fund utilization is typically better in states with higher capacity but lower need. We check whether the past capacity to generate work under MG-NREGA affected the supply of person-days under MG-NREGA during the shutdown and when the restrictions eased. Figure 4.1b plots the correlation between the average number of MG-NREGA person-days generated in 2020 and those generated historically (2014-18) across districts.[9] The plot shows a high positive correlation (0.69) indicating that the districts with historically higher capacity to provide work under MG-NREGA also generated more work under the program when the pandemic struck in 2020.[10] These findings are also in line with Narayanan et al. (2020) who show that the increased MG-NREGA work generation post lockdown was largely correlated with past work generation in a district.

Moreover, we look at the correlation between the historical capacity to provide work under MG-NREGA and state capacity to provide other public goods. We find that generation of MG-NREGA person-days is positively and significantly correlated with an index of provision of other public goods and services at the rural, district-level - education, healthcare, electricity, banking facility and road connectivity (0.16, $p<0.01$). While data are not available on direct measures of state capacity (e.g. revenue generation, or law and order), the positive correlation between MG-NREGA work provision and other public goods suggests that state capacity is an important determinant of the responsiveness of MG-NREGA to adverse shocks in a region. Our results, as we show later, remain robust to controlling for the provision of other public goods in a district.

4.3 Data

We use the Consumer Pyramids Household Survey (CPHS) data from the Centre for Monitoring Indian Economy (CMIE) - a nationwide, household-level panel data where each household is interviewed once every quarter of a year.[11] The CPHS captures employment details and other

[9] We exclude 2019 from the calculation of historical MG-NREGA intensity. The correlation is weighted by the rural population of the district.

[10] Figure 4A.1 in the Appendix shows the historical person-days generated per rural inhabitant by the district. As expected, the states of Rajasthan, Andhra Pradesh (including the regions of present-day Telangana) generated more person-days historically and have been recognized as the best performing states since the inception of the program (Sukhtankar, 2016; Imbert and Papp, 2015).

[11] The CPHS sample is selected through a process of multistage stratification and random sampling of over 98.5% of India's population (Vyas, 2021). It excludes four border states and Union territories (UT) in the North-East, some islands and one small UT on the mainland. We have not used sampling weights in the analysis and we do not claim the findings to be representative of India. In fact, some recent studies have challenged the representativeness of CPHS pointing to the sampling design that under-represents women, young children and the poor (Pais and Rawal,

socio-demographics of individual respondents in the household.[12] The sample of households surveyed in the period Jan-Aug of 2019 was 160,742 which fell by 21.1% during the same period in 2020. Our analysis is, therefore, restricted to a balanced panel of 335,038 individuals residing in 113,812 households, who were surveyed in both 2019 and 2020. Later we check the robustness of our results to household attrition.[13]

Our main outcome of interest is the general employment status of an individual. We use employment data for the working-age population, i.e. individuals aged 15-59 (measured in the quarter Dec 2019-Mar 2020, preceding the shutdown). The CPHS captures the employment status as of the date of the survey. If an individual is engaged in any economic activity either on the day of the survey or on the day preceding the survey or generally regularly engaged in an economic activity she/he is considered employed (even if unable to work in the past few days due to illness or other contingencies). Among the individuals who report themselves to be not employed, the survey further records their alternative status - unemployed, willing and looking for a job; unemployed, willing but not looking for a job; and unemployed, not willing to work and not looking for a job. The CPHS also records the details of employment, including the nature of occupation (19 categories), the industry of occupation (38 categories), type of employment (full time/part-time) and employment arrangement (casual labor, salaried (permanent/temporary), self-employed).

Table 4.1, Panel A, includes the employment statistics for the sample in our analyses at the individual-month-year level. Panel B shows the MG-NREGA person-days of work generated in 2020, 2019 and during 2014-18.[14] Employment rates are higher, on average, in rural areas than urban areas and among men than women.[15]

Note that the CPHS sample size is comparable to the Periodic Labor Force Survey (PLFS) conducted by the Ministry of Statistics and Program Implementation in 2017-18 whose sample size was 102,113 households. Comparison of the employment rates (proportion of people

2021; Somanchi, 2021).

[12] Other modules of the CPHS capture household incomes, assets and monthly expenditure. See Data Appendix for details.

[13] The survey drops those households from the panel that are found missing from their original or expected location. If instead members of a household migrate or are replaced by a new set of members, the household is retained in the panel with the change in the household members marked in the database. Thus, the data do not capture migrant households or members. We later discuss the implications of this for our results.

[14] Individuals' demographic characteristics including location (rural/urban) are measured at the time of the first survey (pre-pandemic). In our analyses, we include data for individuals surveyed both in 2019 and 2020.

[15] Panel A of Appendix Table 4A.1 shows the employment statistics overall and by region and gender, type of employment (Panel B), and unemployment (voluntary vs involuntary in Panel B) during the pre-lockdown period of Jan-Mar 2020 (the period used as the baseline in our analyses).

employed) in the CPHS and the Periodic Labor Force Survey (PLFS) for the months of July 2017-June 2018 shows that for the age group 15-59, the overall employment rate from the CPHS data was 65% for men and 8% for women. The corresponding figures from PLFS using weekly (daily) status were 71% (61%) for men and 20% (14%) for women. Therefore, the employment rates for men are mostly comparable while those for women are almost half for women in the CPHS using weekly status but three-fourths using the daily status definition in PLFS. We compare the PLFS employment rates for rural women (14.5%) and urban women (13.7%) with those in CPHS (12% for rural women and 9% urban women) and find that the difference seems to be higher for urban women. One reason for the difference in women's employment rates could be the framing of the questions across the two surveys. However, the broad patterns across regions for women are similar - lower for urban women than rural women. For further details on the comparison of other demographics of CPHS with the Periodic Labor Force Survey (PLFS) refer to the Data Appendix 4.A.B.

4.4 Estimation Strategy

Using CPHS data for Jan-Aug 2019 and Jan-Aug 2020, we first examine the overall change in employment due to the crisis:

$$y_{icdmt} = \alpha_0 + \alpha_1(Post_m \times Year_{2020}) + D_i + Year_{2020} + M_m + D_{dt} + \epsilon_{icdmt} \quad \text{(3B.1)}$$

where y_{icdmt} is a dummy that takes value one if individual i in occupation c in district d in month m in year t was employed and zero otherwise. $Post_m$ is an indicator variable that takes a value one for the months of April-August, corresponding to the months of national lockdown, and zero otherwise. $Year_{2020}$ is an indicator variable that takes value one for t=2020 and zero otherwise. The above specification is akin to a difference-in-differences strategy where the coefficient (α_1) gives the effect on employment post the shutdown on March 24, 2020. To elaborate, α_1 is the difference between the change in employment between Apr-Aug 2020 - Jan-Mar 2020 and the change in employment between Apr-Aug 2019 - Jan-Mar 2019.

We also account for individual-level heterogeneity (D_i) and seasonality through month fixed effects (M_m) and district-specific year fixed effects (D_{dt}) to allay any concern that the results are driven by district-specific trends over the two years. We examine the overall employment impacts and the dynamic impacts (to estimate recovery) by sub-periods as the stringency of the movement restrictions eased: Phase I (April-May, stringent lockdown), Phase II (June-July, some easing of restrictions) and Phase III (Aug, further easing). Standard errors are clustered at the district-month-year level to account for correlation of shocks to employment within a district in a given month and year.[16]

Next, we examine the effect of MG-NREGA on general employment. To address the concern that contemporaneous person-days generated under MG-NREGA in 2020 are endogenous to the crisis, we exploit the earlier finding that the increase in the provision of person-days under the MG-NREGA during May-August 2020 was higher in districts which on an average in the past have shown greater state capacity in providing employment under the scheme (Figure 4.1b). Thus, we estimate the impact of historical state capacity to provide MG-NREGA work on employment post the shutdown in India using the below specification:

$$\begin{aligned} y_{icdmt} = \beta_0 + \beta_1(Post_m \times Year_{2020} \times NREGA_{dm}) + \\ \delta_1(Post_m \times NREGA_{dm}) + \delta_2(Post_m \times Year_{2020}) + \\ \delta_3(NREGA_{dm} \times Year_{2020}) + D_i + Year_{2020} + M_m + D_{dt} + D_{cmt} + \epsilon_{icdmt} \end{aligned} \tag{3B.2}$$

where $NREGA_{dm}$ is the number of person-days of work in district d in month m generated under MG-NREGA during years 2014-2018, divided by the rural population (as per Census 2011) in the district. Note that our measure of state capacity accounts for the variation in the provision of MG-NREGA workdays with agricultural seasons. The above specification is again akin to a difference-in-differences strategy, with heterogeneous impacts across districts due to differences in historical state capacity to generate MG-NREGA work.[17] The coefficient β_1 gives the effect of an increase in past capacity to generate employment under MG-NREGA by one day per rural inhabitant, on employment, post the shutdown. Thus, a positive value of β_1 would indicate that districts with higher prior state capacity to generate employment under MG-NREGA suffered smaller employment losses post the shutdown. The estimated effect accounts for any seasonal differences in impacts of historical NREGA provision ($Post_m \times NREGA_{dm}$) as well as any overall differential employment trend in areas with higher historical provision of MG-NREGA employment in 2020 vs. 2019 ($NREGA_{dm} \times Year_{2020}$).

The advantage of our estimation strategy is that it allows us to control for seasonal changes in employment, an important consideration in rural areas dependent on agriculture. Notably, as

[16] Our results are robust to alternatively clustering at the district level.

[17] To elaborate, β_1 is the difference between the first difference (i.e. change in employment between Apr-Aug 2020 and Jan-Mar 2020 as historical state capacity increases by one person-day per rural inhabitant) and the second difference (i.e. change in employment between Apr-Aug 2019 - Jan-Mar 2019 as historical state capacity increases by one person-day per rural inhabitant).

we discuss in detail later, the estimation using Equation 3B.1 shows that different occupations witnessed different losses following the lockdown in India. Thus, controlling for occupation-specific time fixed effects (D_{cmt}) in Equation 3B.2 is crucial to identify the effect of differential state capacity to provide MG-NREGA employment, and address any confounding effects of differences in district-specific occupational structures. Here, the occupation status is measured in the quarter preceding the lockdown. This allays any concern that districts with higher historical MG-NREGA person-days are characterised by different occupational/employment structures and hence suffered differential employment changes relative to other districts.[18] Note that the inclusion of occupation-specific month-year fixed effects precludes us from identifying δ_2.

We estimate the above specification - overall and by region, i.e. rural and urban areas separately. While the scheme is applicable only in the rural areas and consequently is expected to have a larger impact there, inter-sectoral linkages through local demand and migration networks may result in spillover of the effects to urban areas. We discuss the implications of inter-sectoral linkages on our results later. We further examine the heterogeneity in the effect of MG-NREGA by gender, given the program's mandate for reserving 1/3rd of jobs for women and existing evidence that suggests women prefer job guarantees more than men.[19]

4.5 Results

4.5.1 Employment trends

We find that overall employment was 5 pp or 12% ($p < 0.01$) lower post the nationwide lockdown in 2020 than in the pre-lockdown months of Jan-Mar 2020, relative to the same difference in 2019 as shown in Panel (a) of Figure 4.2 which plots the coefficient α_1 in Equation 3B.1 for the sample of all individuals aged 15-59.[20] The negative shock to employment did not vary by region, both rural and urban regions experienced a similar negative effect on employment, as indicated in Panel (b), sub-figures 4.2b(i) and 4.2b(ii). While there was a fall in the probability of employment for both men and women post the lockdown relative to their pre-lockdown

[18] We include 15 occupational categories for the employed or those looking for work (viz. Industrial Workers, Wage Laborer, Self-employed, Farmer, Home-based worker), and two categories for those not employed and not looking for work (Home Maker and Others (Retired/Students)). Our results hold even if include a more aggregate occupation classification - Casual, Self-Employed, Salaried, Unemployed, Not in Labor Force (Home Maker and Others (Retired/Students)).

[19] Note that since the objective of the paper is to understand the aggregate impact of the pandemic on employment we do not assess intra-household gender dynamics.

[20] Our estimate lines up with others'. See: Job losses may have narrowed, May 26, 2020, CMIE.

levels (Panel (c), sub-figure 4.2c(i)), after accounting for changes during 2019 over the same period, it was more pronounced for men (8.6 pp or 12% $(p < 0.01)$) than women (0.7 pp or 8% $(p < 0.01)$). The gender differential in the employment effect (7.9 pp) is significant at one percent level as shown in sub-figure 4.2c(ii).

The impact on employment during the entire lockdown period is assessed by phases in Figure 4.3. Panel (a) of Figure 4.3 shows that employment was hit the hardest, by almost 10.9 pp or 26% $(p < 0.01)$, during Phase I of the lockdown in 2020. It was lower by 2.1 pp $(p < 0.01)$ during Phase II, and by Phase III it was almost back to its pre-lockdown levels.

Next, we show the heterogeneity in the employment effects by region and gender in Panel (b) and (c) of Figure 4.3, respectively. Sub-figures 4.3b(i) and 4.3c(i) plot the effects on employment by region and gender, respectively, while sub-figures 4.3b(ii) and 4.3c(ii) plot the difference in these effects across the two demographic groups (difference in coefficients α_1 within region (rural-urban) and gender (women-men), respectively). We find that the fall in employment across all three phases was similar in both rural and urban regions (Figure 4.3, Panel (b)), from the baseline months of Jan-Mar 2020, relative to 2019. However, the gender impacts varied across phases (Figure 4.3, Panel (c)). The magnitude of the gender difference fell with the easing of restrictions as male employment recovered (sub-figure 4.3c(ii)). Note, however, that if we restrict the sample to only those individuals who were employed before the lockdown, the fall in employment is proportionally larger for women than men - in line with Deshpande (2020).

In Table 4.2, we break-down the overall employment impacts by type of labor force engagement. Columns (2)-(4) in Panel A indicate that during the lockdown in 2020, the proportion of casual workers fell by 3.27 pp (22%), followed by salaried (by 1.05 pp or 15%) and lastly the self-employed (by 0.51 pp or 3%). These estimates highlight the heterogeneous impacts of the lockdown by occupation and are in congruence with the survey finding of differential employment effects by type of work in Dhingra and Machin (2020). We find similar occupational differences across the rural and urban sub-samples, reported in Panels B and C, respectively.[21]

4.5.2 Overall effect of MG-NREGA

The first row of Table 4.3 reports the estimates of the effect of historical MG-NREGA state capacity ($NREGA$) following the nationwide lockdown ($Post_m \times Year_{2020}$) on employment

[21] Heterogeneity in the effect of the shock across occupations also holds by gender in rural areas as shown in Appendix Table 4A.2.

(coefficient β_1 in Equation 3B.2).[22] Columns (1) and (2) show the effect for the rural and urban areas, respectively. We find that an additional historical person-day under MG-NREGA per rural inhabitant increased the probability of employment relative to the pre-lockdown months by 3.1 pp (or 7%) in the post lockdown months in the rural areas, relative to 2019 but there was no effect in urban areas (Table 4.3, Columns (1)-(2)). This difference in the effect across rural and urban areas (4.4 pp) is significant at one percent level. Given that the overall loss in rural employment post the shutdown was 5 pp (Table 4.2, Panel B, Column (1)), these estimates suggest that employment losses in areas with higher MG-NREGA state capacity were substantially lower.[23]

Next, we report the dynamic, phase-wise, effects in Table 4.4. The first row reports the coefficients for the most stringent lockdown period of Phase I, and the two subsequent rows report it for the gradual easing in Phase II (Row 2) and Phase III (Row 3), respectively. The triple interaction term in Column (1) indicates that there was a positive but insignificant effect of state capacity in generating MG-NREGA work during the most stringent shutdown period of Phase I (2.9 pp). But with the gradual easing of restrictions, an increase in historical person-days under MG-NREGA by one day per rural person in a district increased the probability of employment in rural areas significantly by 3 and 4.8 pp during Phase II and Phase III of 2020, respectively, from Jan-Mar 2020 and relative to 2019. Since on average districts at the 50^{th} and 95^{th} percentile generated 0.16 and 1.26 person-days of MG-NREGA work per month per rural inhabitant during 2014-18, respectively, the marginal effects indicate cushioning of employment loss when a district shifts from mid to upper end of historical MG-NREGA state capacity distribution. In line with our overall results, we find no significant effect of MG-NREGA in any of the three Phases in urban areas (Column (2)).

We conclude, therefore, that although the impact of state capacity to generate MG-NREGA works was muted immediately following the shutdown, it played a significant role in cushioning job losses in rural areas thereafter. The smaller effect of MG-NREGA state capacity during Phase I could be the result of a fall in actual MG-NREGA person-days generated during late Mar-Apr (strictest shutdown period) in districts that were historically generating greater employment under MG-NREGA (Figure 4.1a). The increase in actual person-days generation was mostly

[22]The interaction of $Post_m \times Year_{2020}$ is subsumed in the occupation time fixed effects. Table 4.2 shows that the impact of the lockdown varies by type of employment and hence the consistency of the estimates on the effect of $NREGA$ after the lockdown rests on inclusion of these as controls.

[23]Among the other double interactions only $Year_{2020} \times NREGA$, showing the overall difference in employment in areas with a higher provision of MG-NREGA employment in 2020 viz-a-viz 2019, has a significantly negative effect. This suggests that there was an overall decline in employment rates over time in districts with greater historical MG-NREGA provision.

during Phase II while in Phase III the increase was around 20% from the baseline.

One concern with our estimation strategy could be that despite the extensive set of controls in our specification, there could still be other unobservable factors correlated with historical state capacity to generate NREGA employment that also vary over time. For instance, a major threat to the validity of our identification strategy could arise from differential inward migration of people across regions post the pandemic due to regional variation in state capacity to provide NREGA employment. There was a massive exodus of workers from urban areas towards their rural homes during Apr-July 2020, and who began returning to the cities in Aug 2020.[24] Although reliable data on migrant workers' movements during this period is absent, it is instructive to discuss how our estimates may be affected by these movements.

First, regions with higher state capacity to generate NREGA are likely to witness a larger increase in the influx of regional migrants for a given out-migration rate before the pandemic. In this case, our estimates, if anything, will be a lower bound on the true effect of past state capacity in reducing employment losses since more workers would be competing for work in these rural areas which have higher state capacity, creating a slack labor market.[25]

Second, pre-pandemic out-migration rates could themselves vary across both high and low historical state capacity regions, even if the proportion of return migrants are comparable between these regions. In this case, if out-migration rates were higher (lower) in districts with historically high MG-NREGA state capacity then our estimates are likely to be lower (upper) bounds of the true impact during April-July; this is because the rural population would have increased relatively more (less) in these districts undermining any increase in the availability of MG-NREGA jobs.

Using the latest available migration data from the National Sample Survey (2007), we find that the correlation between pre-crisis district level seasonal out-migration rates for work in rural areas and historical MG-NREGA annual state capacity is 0.09 ($p<0.05$). Although the correlation is low, given the direction, it suggests that a larger number of migrants moved back to regions with higher historical MG-NREGA state capacity. This suggests that indeed our estimates are likely to be a lower bound on the true effect of prior state capacity on reducing job losses during April-July and an upper bound for August when rural migrants began to return to

[24] Several newspaper reports documented the movement of workers from urban to rural India during April-May 2020. See: At least 23 million migrants are returning to India's villages. Can the rural economy keep up?, May 25, 2020, Scroll; Lockdown in India has impacted 40 million internal migrants: World Bank, April 23, 2020, The Economic Times.

[25] Note that we keep a balanced set of individuals in our analyses who were rural residents before the pandemic, therefore, our results are not sensitive to the movement of people in our sample. The slack labor market would affect the employment rate of these individuals through local district labor market conditions faced by them.

the cities.[26] While the dynamic impact of MG-NREGA may not be entirely attributable to the ability of the state to respond to the crisis (it can reflect the relative movement of the population during this period), since the biases are in two opposite directions, our estimate of the overall impact of the program for the period Apr-Aug 2020 likely reflects the true causal effect of MG-NREGA during the initial months of the pandemic.[27]

Effect of MG-NREGA by gender

We restrict our attention to rural India here, since a positive effect of historical capacity to generate work under MG-NREGA is observed above on rural employment only. Column (3) of Table 4.3 reports the overall effects on rural women while Column (4) lists the effect on rural men. The marginal effect of an increase in average historical person-days under MG-NREGA by one day per rural inhabitant increased the probability of employment for women by 8.6 pp (or by 74% over baseline employment rate) post the lockdown. The overall fall in women's employment in rural areas was 1 pp (Appendix Table 4A.2, Panel D, Column (1)), hence these effects suggest that women who were previously not employed may have entered the workforce in historically high MG-NREGA state capacity areas. While these results are in line with existing literature on the counter cyclicality of women's labor force participation, they also highlight the fact that the availability of suitable employment opportunities can play a role in effectuating it. Examining the dynamic effects by sub-periods on women's employment in rural areas, Column (3) of Table 4.4, shows that MG-NREGA had a significantly positive effect on women's employment in all three phases, which strengthened over time (over 7.6 pp in Phase II and 13.1 pp in Phase III). Conversely, the effect on rural men remains insignificant overall (Table 4.3, Column (4)), as well as, in all three phases ((Table 4.4, Column (4))). Consequently, there exists a significant gender differential in the overall (7.6 pp at one percent significance level) and phase-wise effects of MG-NREGA on employment of women and men.[28]

[26]The reverse movement of workers from rural to urban areas from Aug 2020 is well documented: See No jobs in villages, two-third of migrants return to cities, August 03, 2020, Business Today.

[27]Later we check the robustness of our results to potential effects of state capacity to provide other public goods. Our results remain robust to these more restrictive specifications. Hence, time-varying omitted variables leading to inconsistent estimates is unlikely, though we cannot rule out such confounds completely.

[28]The tests of significance across columns are presented in the rows below the main results. We also examine the effect of NREGA on the intensive margin of employment i.e., on the number of hours worked in a day. However, since data on hours worked is available only from September 2019 we are unable to correct for seasonality in employment using a DID approach. Instead, utilizing data for Jan 2020 - Aug 2020 and computing the single difference or change in average hours of work post the lockdown for rural women as the historical MG-NREGA generation capacity increased by one person per rural inhabitant, we again find a significantly positive effect of MG-NREGA on rural women and an insignificant effect on rural men (Table 4A.3 in Appendix). We also consider

The above results indicate that the effect of historical state capacity in generating women's employment increased as the lockdown restrictions eased. In addition to the lower generation of MG-NREGA works during April-May, this could also be due to women benefiting from lower demand for work as predominantly male migrants moved back to their urban workplace in August. We provide evidence for the latter channel and other possible mechanisms in the next section.

Why did women benefit more from MG-NREGA?

Reservation for women in MG-NREGA jobs and a possibly higher allocation of MG-NREGA person-days to women during the crisis are not sufficient to explain our results (women workers made up for approx. 48.5% of person-days, before and after the pandemic, see Sub-section 4.2.2). Existing literature indicates that women prefer jobs near home due to mobility restrictions, safety concerns and the need to balance care work with market work (Fletcher et al., 2019) as well as a guaranteed job (Dhingra and Machin, 2020). Since MG-NREGA guarantees work within the village precincts it meets many, if not all, of the preferred job characteristics of women.[29]

In order to assess how these supply-side factors may have influenced the impact of the program, we examine the heterogeneous effects of historical MG-NREGA state capacity on employment of rural women by the following individual characteristics in Table 4.5: (Col 1) $Ever\ married$ (dummy variable that takes a value one for women who were ever married, else zero), (Col 2) $Education$ (dummy variable that takes value one for women with education below primary level, else zero) and (Col 3) $Employment$ (dummy equals one for women who were employed in the preceding quarter before the lockdown, else zero) to check whether women already in the labor force or new entrants to the labor market took up MG-NREGA work during the pandemic. We further analyse the heterogeneity of impacts on rural women by household characteristics in Table 4.5: (Col 4) $Young\ children$ (dummy variable that equals one for households with a child up to 12 years of age, else zero) and (Col 5) $Poor$ (takes value one for households in the bottom two deciles of a constructed assets index, else zero). Finally, we examine whether the cushioning of women's employment varied by the proportion of the migrant

an alternative specification wherein we use a binary indicator for median and above historical state capacity instead of the continuous measure of NREGA person-days. The results are similar to our main specification. We find that women in districts with median or above historical MG-NREGA capacity had significantly higher employment with no significant effect on men (results available on request).

[29] Since we account for both time-invariant and time-varying district level heterogeneity in the labor market in our analysis, any difference in employment opportunities (by gender) between high and low capacity districts cannot explain our results.

population of a district, i.e. (Col 6) *Low migrant* - dummy equals one for individuals residing in rural districts without seasonal out-migrant workers, and zero if the district has a positive number of rural out-migrants in the year 2007, the latest year for which such information is available.[30]

The first row of Table 4.5 reports the heterogeneous effects of MG-NREGA by these characteristics on rural women's employment.[31] The second row reports the impact for the base category ($Z = 0$). The row 'Estimate ($Z = 1$)' in the bottom panel reports the sum of the first two rows in the table i.e., the impact for the main category ($Z = 1$). We find that rural women in all these categories ($Z = 0$ as well as $Z = 1$) gained employment in areas with historically high MG-NREGA state capacity but there were significant differences across these categories by marital status, education, children and poverty levels. Column (1) shows that ever-married women's employment increased by 4.5 pp (33%) more than women who were never married and employment of women with primary school-going children increased by 3.9 pp more (33%) than those in households with no child in that age group (Column (4)). These results support the hypothesis that limited mobility and the need to balance child care duties could have led to women accessing a public guarantee program like MG-NREGA more than men.

Similarly, results in Row (1) of Columns (2) and (5) in Table 4.5 indicate that employment of women who were less educated or in households classified as poor increased relatively more due to MG-NREGA by 4.7 pp and 4.9 pp, respectively. However, we do not find any significant difference in employment increase due to MG-NREGA state capacity by previous employment status of women (Column (3)), suggesting that employment of women who were previously employed as well as those who were not increased post-shutdown in regions with historically high MG-NREGA state capacity. We also find that rural women in districts having a low migrant worker population witnessed a larger increase in employment during the Post months due to MG-NREGA state capacity by 11.8 pp (Column (6)). As discussed earlier, this finding can be attributed to lower demand for limited MG-NREGA jobs in low migrant areas, as primarily male migrant workers returned to rural regions post the shutdown.[32]

[30]The marital status is a likely indicator of limited mobility, whether individuals' household has primary school-going children is an indicator of limited mobility and need to balance care work with market work, individuals with lower education and poverty may have a greater preference for guaranteed jobs. For details on the construction of the asset index and calculation of the number of seasonal migrant workers in a district, refer to Appendix 4.A.B.

[31]See Appendix Table 4A.4 for full set of interactions.

[32]We obtain similar results when we analyse contemporaneous work provided under MG-NREGA on changes in employment status of rural women post lockdown and the heterogeneity in these effects. We also examined these heterogeneous impacts on the intensive margin of employment i.e., on the number of hours worked in a day. We continue to find a differentially higher significant effect of MG-NREGA on ever married, less educated women

However, while employment of less-educated men and those in poorer households was cushioned more due to MG-NREGA (Appendix Table 4A.5, Columns (2) and (5)), there were no differential employment effects along the dimensions of marriage or children in the household for rural men (Columns (1), (3) and (4)). Although employment of rural men residing in districts with a low migrant worker population was also cushioned more due to MG-NREGA state capacity (Column (6)), the magnitude of the impact was smaller for men (8 pp for men vs 11.8 pp for women). These results suggest that mobility and child care concerns were additional factors due to which women may have benefited more from MG-NREGA during the crisis.

4.5.3 Robustness Checks

Attrition: We carry out inverse-probability weighted estimation to check the robustness of our results to attrition (see Appendix 4.A.B for methodology), reported in Table 4.6, Columns (1)-(3). The previous conclusions continue to hold - there is a decline in employment post the national lockdown by 5 pp (Column (1)) and historical capacity to generate MG-NREGA works cushions losses for rural women (Column (2)) but not for rural men (Column (3)).

Placebo: We undertake a falsification exercise using data from Jan-Aug 2018 and Jan-Aug 2019 and defining $Year_{2019}$ as t=2019 in Table 4.6. Since there was no pandemic induced shutdown during 2019, we should not see any systematic employment trends for this period. As expected, we find no significant difference between the probability of employment in Apr-Aug 2019, in comparison to Jan-Mar 2019 (Column (4)), relative to that of 2018. The effect of historical state capacity to generate MG-NREGA person-days on rural employment is also not significant in Columns (5) and (6) for either rural women or men.

Other specifications: As discussed above in Section 2.2 above, state capacity to provide public workdays under MG-NREGA is positively correlated with an index of provision of other public goods and services in rural areas like education, healthcare, electricity, banking facility and road connectivity. These characteristics can also directly mediate the impact of the pandemic on employment. We rule this out and show that our results for MG-NREGA state capacity continue to hold even after accounting for these other mediating factors. For this, we construct a district-level index of state capacity. We then check the robustness of our results to the inclusion

and in districts with low migrant workers. The coefficient on children and poor remains positive but is imprecise (Appendix Table 4A.3, Columns (4)-(9)).

of interactions with this index of capacity in a manner similar to our main specification where we have the interactions with MG-NREGA historical state capacity. The results are reported in Table 4A.6 in Appendix. We find that our results on the effect of MG-NREGA state capacity continue to hold even after we control for the heterogeneous employment impacts post the pandemic due to this alternative measure of state capacity of public good provision. Additionally, our results are also robust to controlling for district-month fixed effects to account for seasonality in employment at a geographically disaggregated level. These tables are omitted for brevity and are available on request.

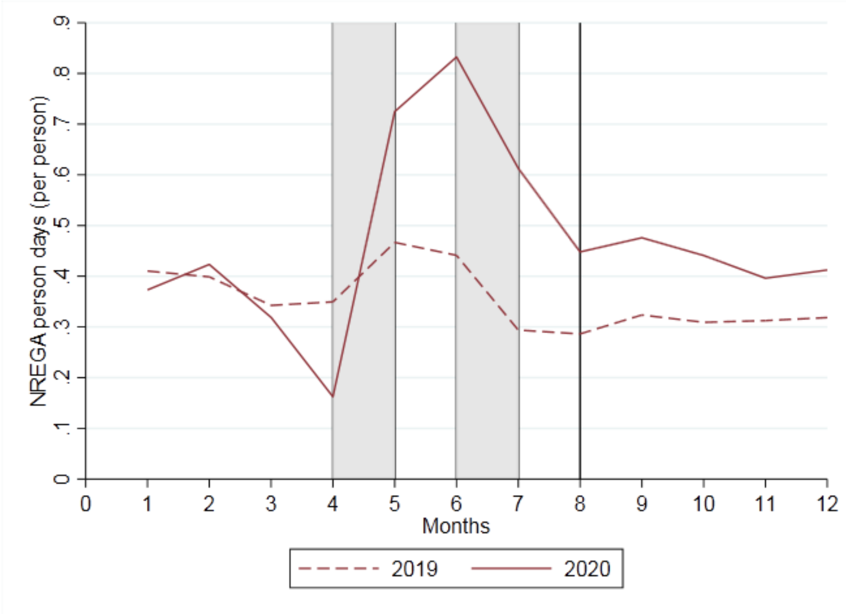
4.6 Conclusion

In this paper, we analyse the extent to which an employment guarantee program was able to stem employment loss in India during the Covid-19 crisis. Using individual-level panel data and accounting for seasonal trends in employment, individual and regional heterogeneity, our findings suggest that districts with higher pre-pandemic capacity to generate public works employment under MG-NREGA were able to cushion job losses significantly in rural areas and more so for rural women. We find no spillover effects on urban employment, highlighting the need for complementary policies in urban areas.[33] Furthermore, rural women who were less likely to be mobile and/or had child care responsibilities gained more from the program, suggesting that the nature of guaranteed jobs can be a critical determinant of which demographic groups benefit from such social protection.

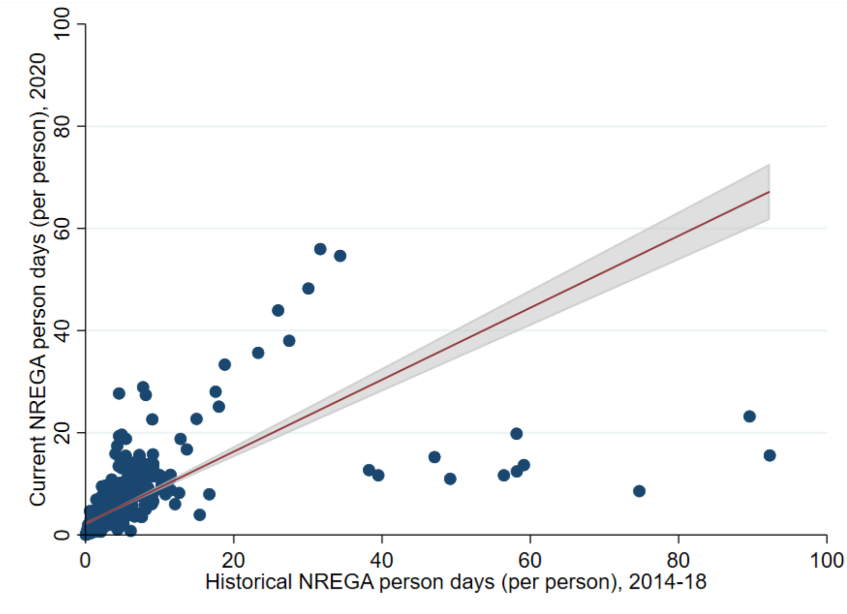
[33] See recent debate on providing an urban MG-NREGA: DUET: A proposal for an urban work programme, Sep 9, 2020, Ideas for India.

4.7 Figures and Tables

Figure 4.1: MG-NREGA person-days per rural inhabitant



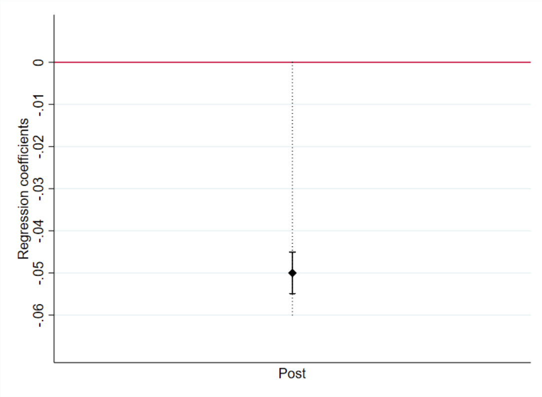
(a) Current



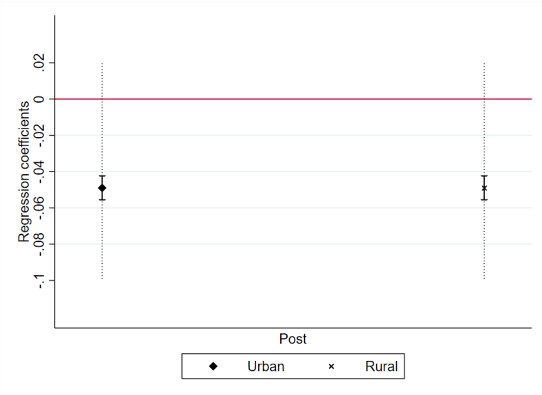
(b) Correlation between current and historical NREGA persondays

Source: NREGA Public Data Portal (2014-2020).
Note: The person-days generated were divided by the rural population of the district (Census 2011). The Historical NREGA in panel (b) is defined using the average historical MG-NREGA person-days generated in a district between 2014-18. 95% confidence interval around the linear fit line.

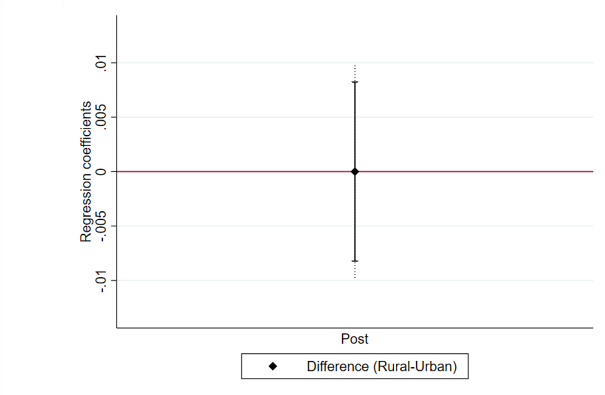
Figure 4.2: Impact of Shutdown on Employment



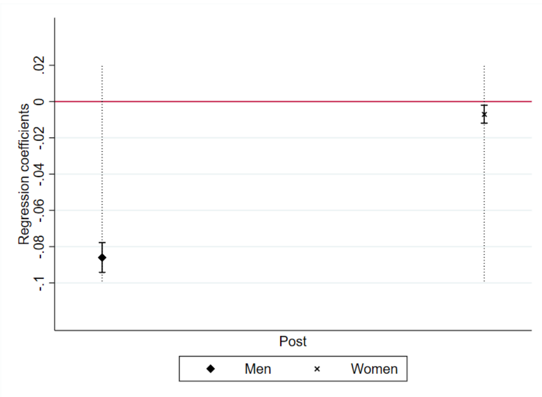
(a) Overall



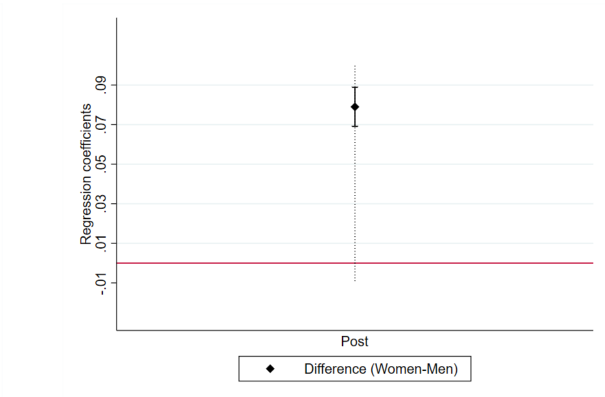
(b(i)) Region



(b(ii)) Difference (Rural-Urban)



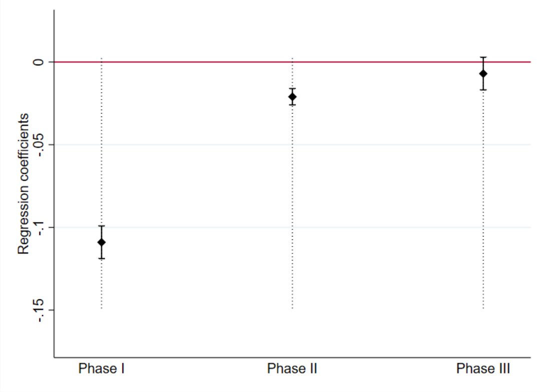
(c(i)) Gender



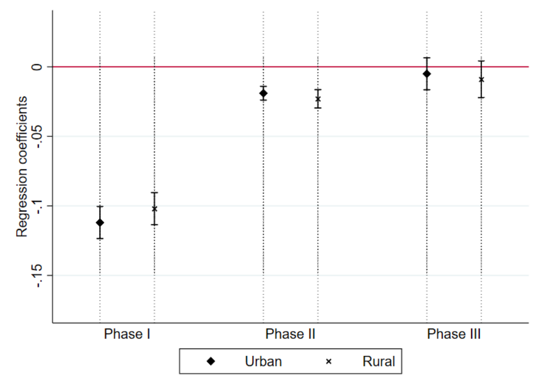
(c(ii)) Difference (Women-Men)

Source: Consumer Pyramids Household Survey Data (2019-2020).
Note: The Figure plots the coefficient α_1 from Equation 3B.1. The classification of the region and gender is as of the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Standard errors clustered at the district-month-year level. 90% confidence bands are plotted around the regression coefficients.

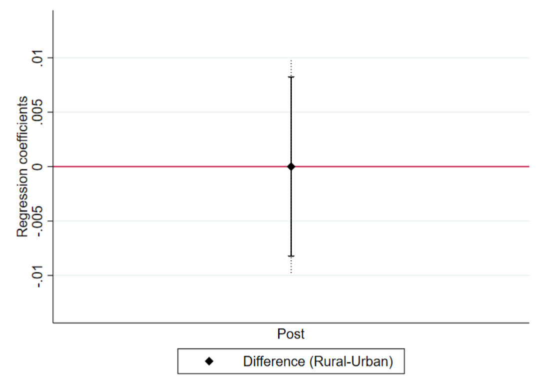
Figure 4.3: Impact of Shutdown on Employment by Phase



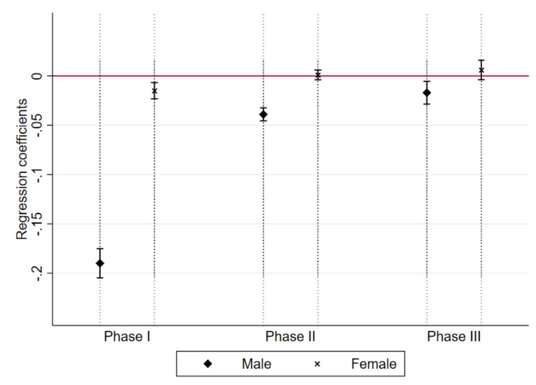
(a) Overall



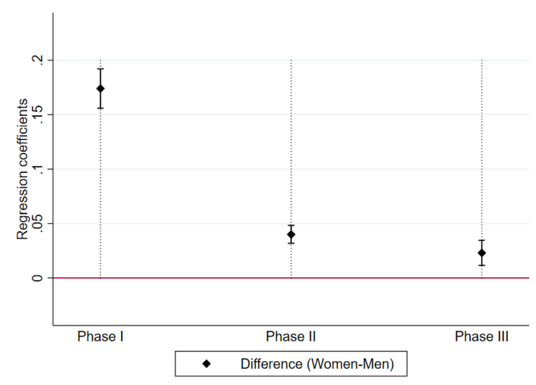
(b(i)) Region



(b(ii)) Difference (Rural-Urban)



(c(i)) Gender



(c(ii)) Difference (Women-Men)

Source: Consumer Pyramids Household Survey Data (2019-2020).
Note: The classification of the region and gender is as per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Standard errors clustered at the district-month-year level. 90% confidence bands are plotted around the regression coefficients.

Table 4.1: Summary Statistics

Panel A: General Employment (Individual-Month-Year level)					
Variable	Number of individuals	Obs	Mean	S.D.	Definition
Overall	335,038	1,040,918	0.41	0.49	Proportion employed
Region					
Rural	114,509	350,907	0.43	0.49	Proportion employed in rural areas
Urban	220,529	690,011	0.40	0.49	Proportion employed in urban areas
Gender					
Men	179,167	557,788	0.65	0.48	Proportion of men employed
Women	155,871	483,130	0.08	0.28	Proportion of women employed
Panel B: MG-NREGA (District-Month level)					
Variable	Number of Districts	Obs	Mean	S.D.	Definition
NREGA 2020	580	4,630	0.49	0.75	Persondays per rural person in 2020
NREGA 2019	580	4,630	0.37	0.62	Persondays per rural person in 2019
Historical NREGA	580	4,630	0.41	0.99	Persondays per rural person in 2014-18

Source: The data for employment is from the Consumer Pyramids Household Survey for the relevant period in the sample (Jan-Aug 2019 and for Jan-Aug 2020). The data for work days (Jan-Aug) generated under MG-NREGA (2014-2020) are taken from NREGA Public Data Portal and normalized by district rural population (Census 2011).

Table 4.2: Impact of Lockdown by Type of Employment

	Employed (1)	Casual (2)	Salaried (3)	Selfemp (4)	Unemp (5)	Not in LF (6)
Panel A: Overall						
$Post_m \times Year_{2020}$	-0.050***	-0.033***	-0.010***	-0.005**	0.034***	0.016***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	1,030,046	1,030,046	1,030,046	1,030,046	1,030,046	1,030,046
R-squared	0.884	0.715	0.771	0.767	0.590	0.877
Mean (Y)	0.42	0.15	0.068	0.195	0.057	0.523
Panel B: Rural						
$Post_m \times Year_{2020}$	-0.049***	-0.038***	-0.011***	0.004	0.032***	0.017***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)
Observations	346,836	346,836	346,836	346,836	346,836	346,836
R-squared	0.884	0.725	0.761	0.797	0.590	0.881
Mean (Y)	0.446	0.166	0.033	0.236	0.049	0.505
Panel C: Urban						
$Post_m \times Year_{2020}$	-0.049***	-0.029***	-0.010***	-0.009***	0.033***	0.015***
	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
Observations	683,210	683,210	683,210	683,210	683,210	683,210
R-squared	0.885	0.710	0.771	0.747	0.591	0.875
Mean (Y)	0.407	0.141	0.087	0.173	0.061	0.533
Fixed Effets						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020).
Note: In all panels, the sample includes individuals aged 15-59 who are classified into one of the employment categories as per their employment status in the pre-pandemic quarter i.e. Dec, 2019-Mar, 2020. The panel B and C have the rural and urban samples, respectively. The Mean (Y) are calculated from the pre-pandemic months of 2020 i.e. Jan-Mar. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4.3: Impact of MG-NREGA on General Employment

	Rural	Urban	Rural	
			Female	Male
	(1)	(2)	(3)	(4)
$Post_m \times Year_{2020}$ × NREGA	0.031**	-0.013	0.086***	0.010
	(0.012)	(0.013)	(0.020)	(0.015)
$Post_m$ × NREGA	-0.002	0.003	-0.008	0.000
	(0.005)	(0.005)	(0.008)	(0.005)
$Year_{2020}$ × NREGA	-0.036***	-0.033**	-0.100***	-0.026
	(0.013)	(0.014)	(0.024)	(0.017)
NREGA	0.000	0.003	0.004	0.002
	(0.005)	(0.006)	(0.008)	(0.007)
Observations	346,836	683,210	159,842	186,993
R-squared	0.891	0.892	0.799	0.850
Mean Y	0.446	0.407	0.116	0.73
Difference ($Post_m$)	0.044***		0.076***	
Fixed Effects				
Individual	✓	✓	✓	✓
Month	✓	✓	✓	✓
Year	✓	✓	✓	✓
Dist × Year	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18) and Census (2011).
Note: The classification of region and gender is as of quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census, 2011) is the measure of historical MG-NREGA. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. The interaction of $Post_m \times Year_{2020}$ is subsumed in the occupation-specific time fixed effects. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e., Jan-Mar 2020. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4.4: Impact of MG-NREGA on General Employment by Phase

	Rural	Urban	Rural	
			Female	Male
	(1)	(2)	(3)	(4)
$Phase_I \times Year_{2020} \times$ NREGA	0.029	-0.012	0.076***	0.011
	(0.021)	(0.018)	(0.029)	(0.025)
$Phase_{II} \times Year_{2020} \times$ NREGA	0.030**	0.002	0.076***	0.013
	(0.013)	(0.013)	(0.021)	(0.015)
$Phase_{III} \times Year_{2020} \times$ NREGA	0.048**	0.015	0.131***	0.031
	(0.024)	(0.027)	(0.040)	(0.031)
$Phase_I \times$ NREGA	0.001	-0.003	0.004	0.001
	(0.007)	(0.005)	(0.011)	(0.008)
$Phase_{II} \times$ NREGA	-0.004	0.005	-0.012	-0.001
	(0.007)	(0.006)	(0.010)	(0.006)
$Phase_{III} \times$ NREGA	0.032**	0.011	0.016	0.041**
	(0.016)	(0.014)	(0.026)	(0.019)
$Year_{2020} \times$ NREGA	-0.029*	-0.024	-0.094***	-0.014
	(0.015)	(0.015)	(0.027)	(0.018)
NREGA	-0.009	-0.000	-0.005	-0.011
	(0.006)	(0.005)	(0.010)	(0.007)
Observations	346,836	683,210	159,839	186,993
R-squared	0.893	0.895	0.802	0.853
Difference ($Phase_I$)	0.041*		0.065*	
Difference ($Phase_{II}$)	0.028		0.063***	
Difference ($Phase_{III}$)	0.033		0.100**	
Fixed Effects				
Individual	✓	✓	✓	✓
Month	✓	✓	✓	✓
Year	✓	✓	✓	✓
Dist × Year	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18) and Census (2011).

Note: The classification of region and gender is as of quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census, 2011) is the measure of historical MG-NREGA. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. The interaction of $Phase_I \times Year_{2020}$, $Phase_{II} \times Year_{2020}$ and $Phase_{III} \times Year_{2020}$ are subsumed in the occupation-specific time fixed effects. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4.5: Heterogenous Impact of MG-NREGA on General Employment of Rural Women

	Individual			Household		District
$Characteristic\ (Z)$	Ever Married	Less Educated	Previously Employed	Young Children	Poor	Low Migrant
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_m \times Year_{2020} \times$ NREGA$\times\ Z$	0.045**	0.047*	0.086	0.039**	0.049*	0.118***
	(0.022)	(0.026)	(0.068)	(0.016)	(0.029)	(0.048)
$Post_m \times Year_{2020} \times$ NREGA	0.049**	0.073***	0.071***	0.073***	0.071***	0.049**
	(0.019)	(0.018)	(0.019)	(0.021)	(0.021)	(0.018)
$Post_m \times Year_{2020} \times Z$	0.019*	0.015*	-0.964***	-0.025***	0.009	-0.029
	(0.011)	(0.008)	(0.142)	(0.005)	(0.009)	(0.014)
$Year_{2020} \times$ NREGA $\times\ Z$	-0.042***	-0.041**	-0.168***	-0.015	-0.017	-0.156***
	(0.016)	(0.016)	(0.040)	(0.010)	(0.019)	(0.051)
Observations	159,842	159,842	159,842	159,842	159,842	154,269
R-squared	0.799	0.799	0.801	0.799	0.799	0.800
Estimate (Z=1)	0.094***	0.12***	0.157***	0.111***	0.121***	0.166***
Mean Y (Z=1)	0.138	0.165	1	0.122	0.155	0.095
Mean Y (Z=0)	0.038	0.101	0	0.112	0.105	0.142
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).
Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e., Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. There are fewer observations in Column (6) because migration data for some districts are missing in NSS 2007. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4.6: Impact of MG-NREGA on General Employment: Robustness

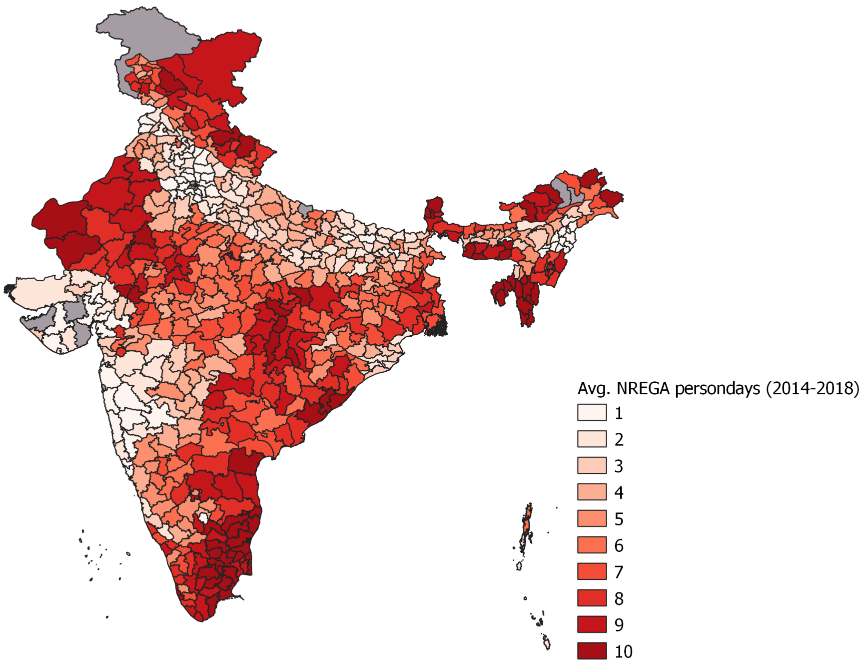
	IPW			Placebo		
		Rural			Rural	
	Overall	Female	Male	Overall	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_m \times Year_{2020}$	-0.050***					
	(0.003)					
$Post_m \times Year_{2020} \times$ NREGA		0.089***	0.008			
		(0.020)	(0.016)			
$Post_m \times Year_{2019}$				-0.001		
				(0.002)		
$Post_m \times Year_{2019} \times$ NREGA					0.017	0.011
					(0.014)	(0.008)
Observations	1,025,526	158,788	185,843	1,141,207	180,884	204,749
R-squared	0.883	0.800	0.849	0.903	0.779	0.879
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓
Occ × Month-Year		✓	✓		✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18) and Census (2011).
Note: Columns (1)-(3) report the Inverse-probability Weighted (IPW) estimates for robustness to attrition and Columns (4)-(6) report the estimates from the placebo check. For attrition, the IPW weights are calculated using the location, PCA of assets owned and observed household characteristics. The classification of region and gender is as of quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Estimates in Column (2)-(3) and (5)-(6) conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. Standard errors clustered at district-month-year level reported in parentheses (**** p<0.01, ** p<0.05, * p<0.1*).

4.A Appendices

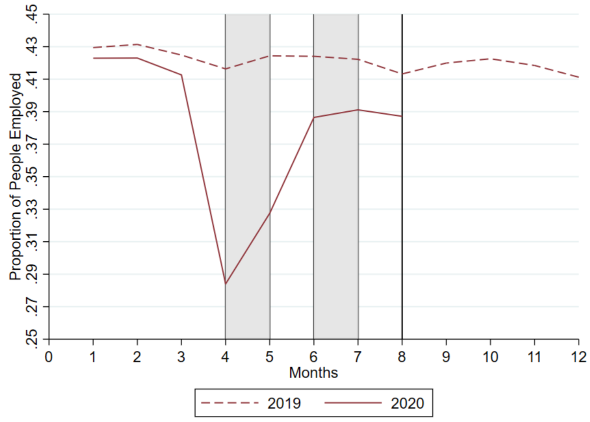
4.A.A Additional Figures and Tables

Figure 4A.1: Average MG-NREGA persondays (2014-18) per rural inhabitant

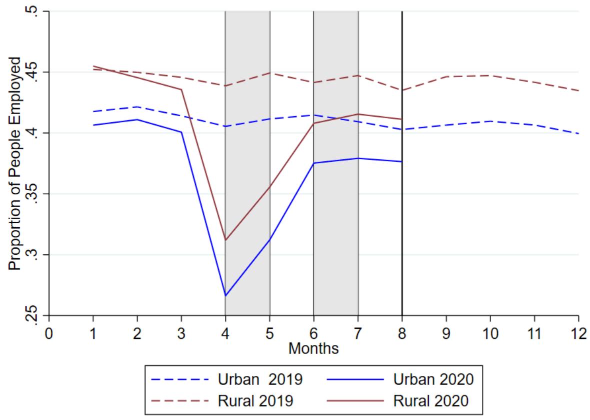


Source: NREGA Public Data Portal (2014-2020).
Note: The districts with missing data for MG-NREGA are colored grey.

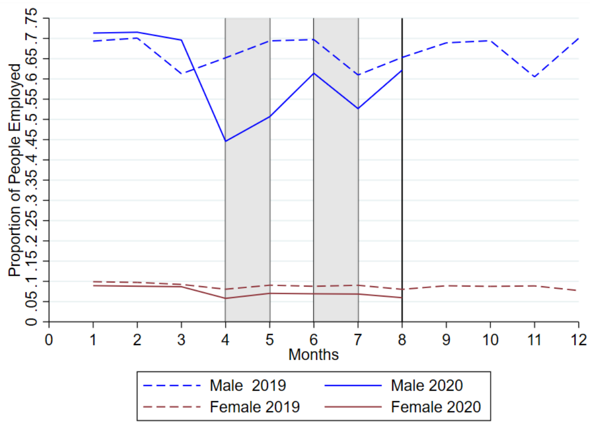
Figure 4A.2: Employment by Year, Region and Gender



(a) Year



(b) Region



(c) Gender

Source: Consumer Pyramids Household Survey (2019-2020).
Note: The classification of region and gender is taken from the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020.

Table 4A.1: Summary Statistics (before national shutdown)

Variable	Obs	Mean	S.D.	Definition
Panel A: General Employment				
Overall	269850	0.42	0.49	Proportion employed
Region				
Rural	92834	0.45	0.50	Proportion employed in rural areas
Urban	177016	0.41	0.49	Proportion employed in urban areas
Gender				
Men	144227	0.71	0.45	Proportion of men employed
Women	125623	0.09	0.28	Proportion of women employed
Gender (Rural)				
Men	49951	0.73	0.44	Proportion of men employed
Women	42883	0.12	0.32	Proportion of women employed
Gender (Urban)				
Men	94276	0.70	0.46	Proportion of men employed
Women	82740	0.07	0.26	Proportion of women employed
Panel B: Employment type				
Casual	269850	0.15	0.36	Daily/monthly wage labour
Salaried	269850	0.07	0.25	Permanent salaried work
Selfemp	269850	0.20	0.40	Self-employed
Unemp (Involuntary)	269850	0.06	0.23	Willing to work but not finding work
Unemp (Voluntary)	269850	0.52	0.50	Not willing to work

Source: Consumer Pyramids Household Survey (2019-2020).
Note: In both the panels, we use the pre-pandemic months of 2020 i.e. January-March. The sample includes all individuals aged 15-59.

Table 4A.2: Impact of Lockdown by Type of Employment

	Employed (1)	Casual (2)	Salaried (3)	Selfemp (4)	Unemp (5)	Not in LF (6)
			Panel A: Rural Female			
$Post_m \times Year_{2020}$	-0.010*	-0.008**	-0.003***	0.001	0.013***	-0.003
	(0.005)	(0.004)	(0.001)	(0.003)	(0.004)	(0.006)
Observations	159,843	159,843	159,843	159,843	159,843	159,843
R-squared	0.769	0.710	0.775	0.724	0.634	0.752
Mean (Y)	0.116	0.057	0.009	0.05	0.033	0.851
			Panel B: Rural Male			
$Post_m \times Year_{2020}$	-0.083***	-0.064***	-0.018***	0.006	0.049***	0.034***
	(0.006)	(0.007)	(0.003)	(0.006)	(0.006)	(0.004)
Observations	186,993	186,993	186,993	186,993	186,993	186,993
R-squared	0.841	0.708	0.756	0.762	0.576	0.832
Mean (Y)	0.73	0.26	0.054	0.396	0.062	0.208
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020).
Note: In all panels, the sample includes individuals aged 15-59 who are classified into one of the employment categories as per their employment status in the pre-pandemic quarter i.e. Dec, 2019-Mar, 2020. Panel A and B have the female and male sample from rural regions, respectively. The Mean (Y) are calculated from the pre-pandemic months of 2020 i.e. Jan-Mar. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4A.3: Impact of MG-NREGA on Hours Worked

	Rural			Rural Women Hetero (Z)					
				Individual			Household		District
	Overall	Female	Male	Ever Married	Less Educated	Previously Employed	Young Children	Poor	Low Migrant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Post_m \times Year_{2020} \times$ NREGA	0.158	0.441***	0.028						
	(0.143)	(0.131)	(0.246)						
$Post_m \times Year_{2020} \times$ NREGA $\times Z$				0.272*	0.427**	0.584	0.251	0.340	0.563***
				(0.156)	(0.217)	(0.467)	(0.173)	(0.234)	(0.294)
Observations	90,672	41,558	49,114	41,558	41,558	41,558	41,558	41,558	39,896
R-squared	0.856	0.820	0.792	0.820	0.820	0.823	0.820	0.820	0.818
Mean Y	3.443	0.798	5.714						
Mean Y (Z=1)				1.045	1.137	6.888	0.853	1.083	0.657
Mean Y (Z=0)				0.292	0.696	0	0.776	0.721	0.976
Fixed Effects									
Individual	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).
Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e. Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. There are fewer observations in Column (9) because migration data for some districts were missing. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4A.4: Heterogenous Impact of MG-NREGA on General Employment of Rural Women

	Individual			Household		District
$Characteristic\ (Z)$	Ever Married (1)	Less Educated (2)	Previously Employed (3)	Young Children (4)	Poor (5)	Low Migrant (6)
$Post_m \times Year_{2020}$ × NREGA × Z	0.045**	0.047*	0.086	0.035*	0.049*	0.118**
	(0.022)	(0.026)	(0.068)	(0.018)	(0.029)	(0.048)
$Post_m \times Year_{2020}$ × NREGA	0.049**	0.073***	0.071***	0.077***	0.071***	0.049***
	(0.019)	(0.018)	(0.019)	(0.020)	(0.021)	(0.018)
$Post_m$ × NREGA× Z	-0.004	0.018	0.028	-0.003	-0.005	0.018
	(0.014)	(0.014)	(0.041)	(0.010)	(0.014)	(0.016)
$Post_m \times Year_{2020} \times Z$	0.019*	0.015*	-0.964***	-0.024***	0.009	-0.029**
	(0.011)	(0.008)	(0.142)	(0.006)	(0.009)	(0.014)
$Year_{2020}$ × NREGA × Z	-0.042***	-0.041**	-0.168***	-0.014	-0.017	-0.156***
	(0.016)	(0.016)	(0.040)	(0.010)	(0.019)	(0.051)
$Post_m \times Z$	-0.003	-0.006	0.113	0.009**	0.001	-0.014*
	(0.007)	(0.005)	(0.082)	(0.004)	(0.005)	(0.008)
$Year_{2020} \times Z$	-0.021***	-0.011**	0.842***	0.022***	-0.014**	
	(0.008)	(0.005)	(0.083)	(0.003)	(0.006)	
$Post_m$ × NREGA	-0.004	-0.012	-0.013	-0.007	-0.006	-0.017
	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)
$Year_{2020}$ × NREGA	-0.067***	-0.091***	-0.070***	-0.096***	-0.087***	-0.050***
	(0.026)	(0.023)	(0.021)	(0.023)	(0.023)	(0.018)
NREGA× Z	0.007	-0.011	-0.065*	-0.008	0.005	-0.011
	(0.014)	(0.018)	(0.036)	(0.015)	(0.017)	(0.015)
NREGA	-0.001	0.006	0.015*	0.007	0.002	0.012
	(0.010)	(0.008)	(0.008)	(0.009)	(0.011)	(0.011)
Observations	159,842	159,842	159,842	159,842	159,842	154,269
R-squared	0.799	0.799	0.801	0.799	0.799	0.800
Estimate (Z=1)	0.094***	0.12***	0.157***	0.111***	0.121***	0.166***
Mean Y (Z=1)	0.138	0.165	1	0.122	0.155	0.095
Mean Y (Z=0)	0.038	0.101	0	0.112	0.105	0.142
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).
Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e., Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. The interaction of $Post_m \times Year_{2020}$ is subsumed in the occupation-specific time fixed effects. In Column (6), the interaction of $Year_{2020} \times Z$ is absorbed in the District year fixed effects as migration is defined at the district level and there are fewer observations because migration data for some districts are missing in NSS 2007. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4A.5: Heterogenous Impact of MG-NREGA on General Employment of Rural Men

	Individual			Household		District
$Characteristic\ (Z)$	Ever Married	Less Educated	Previously Employed	Young Children	Poor	Low Migrant
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_m \times Year_{2020} \times$ NREGA $\times Z$	-0.018	0.053***	0.003	0.021	0.075***	0.080***
	(0.025)	(0.020)	(0.026)	(0.016)	(0.024)	(0.031)
$Post_m \times Year_{2020} \times$ NREGA	0.026	0.001	0.006	0.008	-0.007	-0.018
	(0.021)	(0.015)	(0.021)	(0.016)	(0.017)	(0.020)
$Post_m \times$ NREGA$\times Z$	0.009	-0.002	-0.002	0.009	-0.011	-0.011
	(0.013)	(0.011)	(0.015)	(0.009)	(0.012)	(0.011)
$Post_m \times Year_{2020} \times Z$	0.318***	0.030***	-105***	0.068***	0.009	-0.021
	(0.016)	(0.011)	(0.051)	(0.008)	(0.011)	(0.014)
$Year_{2020} \times$ NREGA $\times Z$	0.002	-0.005	-0.065***	0.001	-0.002	-0.128***
	(0.014)	(0.011)	(0.016)	(0.009)	(0.014)	(0.035)
$Post_m \times Z$	-0.047***	-0.010*	0.053**	-0.008*	-0.001	0.004
	(0.009)	(0.006)	(0.024)	(0.004)	(0.006)	(0.005)
$Year_{2020} \times Z$	-0.228***	-0.041***	0.978***	-0.050***	-0.021***	
	(0.011)	(0.006)	(0.027)	(0.004)	(0.007)	
$Post_m \times$ NREGA	-0.006	0.001	0.002	-0.002	0.002	0.002
	(0.011)	(0.006)	(0.013)	(0.006)	(0.006)	(0.006)
$Year_{2020} \times$ NREGA	-0.037*	-0.024	0.028	-0.025	-0.016	0.017
	(0.020)	(0.017)	(0.021)	(0.017)	(0.018)	(0.023)
NREGA$\times Z$	0.020	0.008	-0.002	-0.016	-0.006	0.005
	(0.017)	(0.012)	(0.018)	(0.010)	(0.013)	(0.014)
NREGA	-0.008	0.001	0.003	0.006	0.003	0.001
	(0.013)	(0.008)	(0.016)	(0.008)	(0.009)	(0.009)
Observations	186,993	186,993	186,993	186,993	186,993	180,375
R-squared	0.855	0.850	0.852	0.850	0.850	0.849
Estimate (Z=1)	0.008	0.054***	0.009	0.025	0.068***	0.062***
Mean Y (Z=1)	0.964	0.909	1	0.88	0.755	0.728
Mean Y (Z=0)	0.381	0.709	0	0.666	0.724	0.732
Fixed Effects						
Individual	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
District × Year	✓	✓	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18), Census (2011) and Employment and Unemployment Survey, NSS (2007).
Note: The classification of all characteristics is per the quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. Ever married indicates individuals who were ever married. Less Educated is indicator for below primary education. Previously Employed is indicator for those employed. Young Children indicates households with children aged upto 12 years of age and Poor indicates households falling in the bottom two deciles of the distribution of PCA of assets owned by a household. Low migrant is indicator for districts that have no out-migrants (NSS, 2007). The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census 2011) is the measure of historical MG-NREGA. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e. Jan-Mar 2020. Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. The interaction of $Post_m \times Year_{2020}$ is subsumed in the occupation-specific time fixed effects.In Column (6), the interaction of $Year_{2020} \times Z$ is absorbed in the District year fixed effects as migration is defined at the district level and there are fewer observations because migration data for some districts are missing in NSS 2007. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4A.6: Robustness: Controlling for Alternative Measure of State Capacity

	Rural	Urban	Rural	
			Female	Male
	(1)	(2)	(3)	(4)
$Post_m \times Year_{2020} \times$ NREGA	0.023*	-0.017	0.082***	0.001
	(0.012)	(0.014)	(0.020)	(0.015)
$Post_m \times Year_{2020} \times$ Capacity	0.018***	-0.002	0.021***	0.023***
	(0.005)	(0.004)	(0.004)	(0.008)
$Post_m \times$ NREGA	-0.002	0.003	-0.007	-0.001
	(0.005)	(0.005)	(0.009)	(0.005)
$Post_m \times$ Capacity	-0.003	-0.000	-0.005***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$Year_{2020} \times$ NREGA	-0.031**	-0.030**	-0.097***	-0.020
	(0.014)	(0.014)	(0.024)	(0.017)
NREGA	0.001	0.003	0.004	0.003
	(0.006)	(0.006)	(0.008)	(0.007)
Observations	329,123	642,159	151,523	177,599
R-squared	0.891	0.892	0.799	0.849
Mean Y	0.446	0.407	0.116	0.73
Difference NREGA ($Post_m$)	0.041**		0.080***	
Difference Capacity ($Post_m$)	0.020***		-0.001	
Fixed Effects				
Individual	✓	✓	✓	✓
Month	✓	✓	✓	✓
Year	✓	✓	✓	✓
Dist × Year	✓	✓	✓	✓
Occ × Month-Year	✓	✓	✓	✓

Source: Consumer Pyramids Household Survey (2019-2020), NREGA Public Data Portal (2014-18) and Census (2011).
Note: The classification of region and gender is as of quarter preceding the pandemic i.e. Dec, 2019-Mar, 2020. The average monthly persondays generated under MG-NREGA in the last five years (i.e. between 2014-18) per rural inhabitant (Census, 2011) is the measure of historical MG-NREGA. 'Capacity' an index of state Capacity (i.e. PCA index of provision of public goods and services mentioned above). Estimates conditional on differential trends across occupation, with individuals' occupation measured in the quarter preceding the pandemic. The interaction of $Post_m \times Year_{2020}$ is subsumed in the occupation-specific time fixed effects and $Year_{2020} \times Capacity$ is subsumed in the District-specific time fixed effects. Mean (Y) refers to the mean of the dependent variable in the months before the national lockdown i.e., Jan-Mar 2020. Standard errors clustered at district-month-year level reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

4.A.B Data Appendix

CPHS vs. PLFS

In the CPHS 84% of households follow the Hindu religion, 10% are Muslims and the remaining are composed of other religions in CPHS. The caste composition of the sample is as follows: 21% Scheduled Classes (SC), 6% Scheduled Tribes (ST) and 39% Other Backward Classes (OBC). The remaining 34% is constituted by other caste categories. These figures are very similar to those reported in PLFS-2017-18.

Asset Index

We construct binary indicators of ownership of assets in the quarter preceding the crisis i.e. December 2019-March 2020, that equals one for households that own it and zero otherwise. These include - ownership of refrigerator, air conditioner, cooler, washing machine, television, computer, car, two-wheeler, inverter, tractor and cattle. We then use the Principal Components Analysis (PCA) to generate the asset index (the first principal component) over these indicators. We generate deciles of the asset index separately for rural and urban regions. The households falling in the bottom two deciles of this distribution, for their respective region, are classified as poor households.

Migration

We use the NSS Employment and Unemployment Survey 64^{th} Round (2007-08) to construct a measure of district level, rural seasonal out-migrants. NSS records data on the members of the household that were away from home in search of work for up to six months. We take a weighted sum of the number of household members residing in rural areas that migrated for work from a district. This provides us migration data for 470 Districts of the total of 502 Districts for which CPHS data (2019-20) is available. For the remaining districts, out-migration data could not be mapped to the CPHS districts and is thus missing. We use this measure of rural seasonal out-migrants to construct an indicator for low migration districts. 'Low migrant' district takes value one when the reported number of out-migrants are nil and zero otherwise. 64% of the districts in our analysis are low migrant districts.

Inverse-probability weights

A total of 156,269 unique households were surveyed in January-August, 2019 and of these 79% were present in January-August, 2020. We follow the standard Inverse-probability weighting (IPW) approach which corrects for selection bias under the assumption that selection is determined by observed household characteristics. We estimate the selection probabilities i.e., the probability of being present in 2020 for a household that was surveyed in 2019 using the pre-pandemic location (rural/urban) of the household, the constructed asset index and other observed household characteristics. Household characteristics include - ownership of mobile phone by any member of the household, age group (based on the distribution of members of a household by their age), income group (based on the annual income of the household i.e. the income of all its members from all sources during 12 months), occupation group (based on the composition of the members of the household by the nature of their occupation), education group (based on the composition of the maximum education level of household members who are 25 years of age or more), gender group (based on the distribution of members of a household by their gender), water access group (based on the number of hours that a household receives water during a day), power access group (based on the number of hours that a household receives continuous electricity) and family size group (based on the number of members in a household). These predicted probabilities are then used to generate the inverse probability weights for attrition correction. Each household in the analysis is then weighted by these inverse probabilities of being surveyed in 2020. While this approach addresses selection on observables, it cannot rule out the selection on other unobserved or dynamic characteristics.

Chapter 5

Conclusion

In conclusion, this thesis has examined the supply and demand side constraints to women's labor force participation. The study highlights the role of gendered social networks and norms in the adoption of digital technologies and the potential of information on employment opportunities to relax norms around women's work outside home.

The research indicates the significant social costs faced by women in taking up work outside the home which may not be fully offset by a reduction of job search cost. Domestic chores and childcare responsibilities limit the mobility of women and result in high reservation wages. Faced with these constrains and the narrow home-bound social networks, they continued to conform to the norm of home-based work. The husbands network structure enhanced their labor market participation, work intensity, and earnings. From a policy perspective, our findings underscore the importance of keeping the network structure in the policy framework to enhance the labor force participation of women.

Furthermore, our research shows that in the context of these social networks and norms, shocks to the labor market exacerbate the extant gender disparities. Women suffer a double whammy as they are impacted more by negative productivity shocks and lack access to coping mechanisms to offset there adverse effects.

Social protection programs, like employment guarantees with a special focus on women, can play a crucial role in stemming job losses and aiding recovery, especially for mobility-constrained women. However, the effectiveness of these policies depends on state capacity, which is a critical player in the development process.

In sum, this study highlights the need for policymakers to recognize the social norms and institutional constraints that limit women's participation in the labor market. Addressing these challenges requires a multifaceted approach that considers the role of networks, information sharing, and social protection programs, while also recognizing the critical importance of state capacity.

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Appendix I

RCT questionnaires (Chapter 4)

Household Survey

Field	Question	Answer
General Household Information घर की सामान्य जानकारी		
	Instructions: Please address the following questions to the respondent. The respondent for this questionnaire should ideally be the household head. But if the household head is not available any knowledgeable adult in the household, either male or female, can be interviewed. निर्देश: कृपया निम्नलिखित प्रश्न उत्तरदाता से पूछें। इस प्रश्नावली के लिए उत्तरदाता आदर्श रूप से घर का मुखिया होना चाहिए। लेकिन अगर घर के मुखिया घर में उपलब्ध नहीं है, तो कोई जानकार वयस्क, पुरुष या महिला, का साक्षात्कार लिया जा सकता है।	
-	Kindly ask the respondent for the full address of their household. कृपया प्रतिवादी से घर का पूरा पता पूछें।	
General Household Information > Household Address घर की सामान्य जानकारी > घर का पता		
15A	Name of the Block ब्लॉक	
15B	House Number घर का नम्बर	
15C	Floor Number (Enter 0 for Ground floor) फ्लोर नंबर (ग्राउंड फ्लोर के लिए 0 डालें)	
15D	Name of the Colony कॉलोनी का नाम	
15E	Gali Number गली नम्बर	
General Household Information > Respondent's Name घर की सामान्य जानकारी > उत्तरदाता का नाम		
16	What is youe full name? आपका पूरा नाम क्या है?	
16A	First Name प्रथम नाम	
16B	Last Name/ Surname पारिवारिक नाम/कुल नाम	
General Household Information > Household Head's Name घर की सामान्य जानकारी > घर के मुखिया का नाम		
17	What is the name of the household head? घर के मुखिया का नाम क्या है?	
17A	First Name प्रथम नाम	
17B	Last Name / Surname पारिवारिक नाम/कुल नाम	
18	Specify your jati. अपनी जाति बताइए।	
19	Which of the categories do you consider yourself in? आप खुद को इनमें से किस श्रेणी में मानते हैं?	1 SC अनुसूचित जाति (एस सी) 2 ST अनुसूचित जन जाति (एस टी) 3 OBC अन्य पिछड़ा वर्ग (ओ बी सी) 4 General जनरल 777 Other अन्य

Field	Question	Answer
		999 Don’t know/ Cant say पता नहीं / बता नहीं सकते
20	Specify the other category अन्य हैं, तो कृपया स्पष्ट करें।	
21	What is your religion? आपका धर्म क्या है?	1 Hindu हिन्दू 2 Muslim मुस्लिम 3 Christiam ईसाई 777 Other अन्य 999 Don’t know/ Cant say पता नहीं / बता नहीं सकते
22	Specify the other religion अन्य हैं, तो कृपया स्पष्ट करें।	
23	What are the languages spoken in this house? (Select multiple options, if any) इस घर में कौन सी भाषाएँ बोली जाती हैं? (कई विकल्पों का चयन करें, यदि कोई हो)	1 Hindi हिंदी 2 Urdu उर्दू 3 Bhojpuri भोजपुरी
24	Specify the other languages spoken. अन्य हैं, तो कृपया स्पष्ट करें।	
25	Which state does the household head originally comes from? घर के मुखिया किस राज्य से मूल रूप से आते हैं?	
26	Which district does the household head originally comes from? घर के मुखिया किस जिल्ले से मूल रूप से आते हैं?	
27	For how many years has your family been living in current location? आपका परिवार कितने सालो से वर्तमान स्थान पर रह रहे हैं?	
28	What is the type of your house? आपके घर का प्रकार क्या है?	Pucca पक्का Semi-Pucca आधा पक्का Katcha कच्चा Don’t know/Cant say पता नहीं / बता नहीं सकते
29	Do you or any other family member own this plot of land of your house? क्या आप या आपके परिवार का कोई सदस्य इस घर की जमीन के मालिक हैं?	Yes हाँ No नहीं Don’t know/ Cant say पता नहीं / बता नहीं सकते

Field	Question	Answer
30	Are you or any other family member the original owner of this land? क्या इस भूमि के असली/पहले/मूल मालिक हैं?	Yes हाँ No नहीं Don't know/Cant say पता नहीं / बता नहीं सकते
31	Do you or any other family member own this apartment/flat? क्या आप इस अपार्टमेंट/ फ्लैट के मालिक हैं?	Yes हाँ No नहीं Don't know/Cant say पता नहीं / बता नहीं सकते
32	Is your family renting this flat/apartment? तो क्या आपका परिवार इस फ्लैट/अपार्टमेंट में किराए पर रहते हैं?	Yes हाँ No नहीं Don't know/Cant say पता नहीं / बता नहीं सकते
33	What is the electrification Status of the house? घर की बिजली की स्थिति क्या है?	Electrified बिजली है Not electrified बिजली नहीं है Other अन्य
34	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
35	What is the sanitation facility used by the people in this household? इस घर में लोगों द्वारा उपयोग की जाने वाली स्वच्छता/शौचालय सुविधा क्या है?	Private pit-latrine निजी पिट-शौचालय Community Toilet समुदाय शौचालय Open defecation खुले में शौच Other अन्य
36	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
37	On which water supply source does your family usually depend on? पानी के किस स्रोत पर परिवार निर्भर करता है?	Public tap सार्वजनिक नल Handpump हेडपम्प Water Tank पानी की टंकी Private household tapwater connection निजी घरेलू नल कनेक्शन Other अन्य
38	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
39	Do you have a ration card? क्या आपके परिवार के पास राशन कार्ड है?	Yes हाँ No नहीं Don't know/Cant say पता नहीं / बता नहीं सकते
40	What type of ration card does your household have? (Investigator, please ask for respondent's ration card and verify response. Note ration card of head if multiple ration cards.)	PR पी आर PRS पी आर एस Antyodaya Anna Yojana (Red) अंत्योदय अन्न योजना (लाल) Other अन्य

Field	Question	Answer
	राशन कार्ड का प्रकार (कृपया उत्तरदाता के राशन कार्ड के लिए पूछें और जवाब की पुष्टि करें। यदि एक से ज़्यादा राशन कार्ड है तो मुखिया के राशन कार्ड को देखें।)	
41	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
Details of the household members घर के सदस्यों का विवरण		
	Following information is to be collected for those members who regularly reside with this family, are currently residing and eat from same kitchen. निम्नलिखित प्रश्न परिवार के उन सदस्यो के बारे में हैं जो आम-तौर पर इस परिवार के साथ रहते हैं या वर्तमान में यहां रह रहे हैं और एक रसोई से खाना खाते हैं।	
	Enter the details of the head of the HH in the first row, followed by details of the other members of the HH. पहली पंक्ति में घर के प्रमुख का विवरण दर्ज करें, उसके बाद घर के अन्य सदस्यों का विवरण।	
Details of the household members > Demographic Composition of the household (1) घर के सदस्यों का विवरण > घर की जनसांख्यिकी रचना (1)		(Repeated group)
42	Individual ID व्यक्ति ID	
43	Name नाम	
44	Relationship with household head घर के मुखिया के साथ सबंध	1 The household head घर के मुखिया 2 Spouse पति/पत्नी 3 Son/Daughter पुत्र/पुत्री 4 Father/Mother पिता/माँ 5 Son-in-law/Daughter-in-law दामाद/बहू 6 Brother/Sister भाई/बहन 7 Father-in-law/Mother-in-law ससुर/सास 8 Grandparent दादा/दादी/नाना/नानी 9 Grandchild पोता/पोती/नाती/नातिन 10 Sister-in-law/Brother-in-law भाभी/देवरानी/जेठानी/ननद/जेठ/देवर/नन्दोई/जीजा 11 Nephew/Niece भतीजा/भतीजी/भांजा/भांजी 777 Other अन्य
45	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
46	Gender लिंग	1 Male पुरुष 2 Female महिला
47	Age (in years) (Enter 0 for infants) आयु (सालों में) (शिशु के लिए 0 डालें)	

Field	Question	Answer
48	Age (in months for infants) आयु (महीनों में, केवल शिशु के लिए)	
49	Marital status वैवाहिक स्थिति	1 Unmarried अविवाहित 2 Married शादीशुदा 3 Widowed विधवा/विधुर 4 Divorced तलाकशुदा 5 Separated पति/पत्नी से अलग
50	Couple ID जोड़ा ID	
51	Education Level शिक्षा स्तर	0 Not Educated कोई पढ़ाई नहीं की 1 1st class पहली कक्षा 2 2nd class दूसरी कक्षा 3 3rd class तीसरी कक्षा 4 4th class चौथी कक्षा 5 5th class पांचवीं कक्षा 6 6th class छट्टी कक्षा 7 7th class सातवी कक्षा 8 8th class आठवीं कक्षा 9 9th class नवमी कक्षा 10 10th class दसवीं कक्षा 11 11th class ग्यारवही कक्षा 12 12th class बारवीं कक्षा 13 Graduate ग्रेजुएट (BA/BSc/BEd/BCA) 14 Uncompleted Graduate degree अधूरा ग्रेजुएट 15 Post Graduate पोस्ट ग्रेजुएट (MA/MSc/MCA) 16 Graduate & uncompleted postgraduate degree अधूरा पोस्टग्रेजुएट 17 Diploma or technical training, specify डिप्लोमा या तकनीकी प्रशिक्षण, स्पष्ट करें 777 Other, specify अन्य, स्पष्ट करें
52	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
53	If diploma or technical training, please specify अगर डिप्लोमा या तकनीकी प्रशिक्षण, स्पष्ट करें	
54	Occupation मुख्य व्यवसाय	1 Wage labourer in factories मजदूरी (कारखानों/फैक्ट्री में) 2 Wage labourer in construction मजदूरी (कंस्ट्रक्शन/बेलदारी में) 3 Wage labourer in domestic work मजदूरी (घरों में सफाई/खाना बनाने का काम) 4 Casual Labour in other मजदूरी (अन्य) 5 Self- employed in retail activities स्व-रोज़गार (रीटेल)

Field	Question	Answer
		6 Self- employed in own business manufacturing स्व-रोज़गार (उद्योग) 7 Self- employed in other स्व-रोज़गार (अन्य) 8 Salaried employee at non-govt (or private) नौकरी (गैर सरकारी (non-govt or private)) 9 Salaried employee at government नौकरी (सरकारी) 10 Housewife गृहिणी 11 Unemployed बेरोजगार 12 Student छात्र/छात्रा 13 Cannot work due to disability/ ill-health विकलांगता / अस्वस्थता के कारण काम नहीं कर सकते 14 Retired रिटायर्ड (Retired) 15 Too young to work काम करने के लिए बहुत छोटी उम्र 777 Other अन्य
55	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
Selection for individual questionnaire व्यक्तिगत प्रश्नावली के लिए चयन		
56	Just to clarify: is [fam_name1] the household head? सर्वेक्षणकर्ता, फिर से पुष्टि करने के लिए पूंछे: क्या [fam_name1] इस परिवार के मुखिया हैं ?	1 Yes हाँ 0 No नहीं
couple_selection_note	From the household roster, choose a young couple for the individual survey on the following criterion: (a) select the couple for whom the sum of their ages is the least amongst all couples. If there is more than one couple with same minimum sum of ages, then select based on the second criteria. (b) For the couples with the same minimum age, look at the ages of the females and select the female member who has the youngest age. Select her and her husband for the survey. घरेलू रोस्टर से, निम्न मानदंड पर व्यक्तिगत सर्वेक्षण के लिए एक युवा जोड़े को चुनें : (1) उस जोड़े को चुनें जिनकी उम्र का जमा सभी जोड़ों में सबसे कम है। यदि एक से अधिक जोड़े हैं जिनकी उम्र का जमा बराबर है और सबसे कम है, तो दूसरे मानदंड के आधार पर चुनें । (2) सबसे कम और बराबर उम्र वाले जोड़ों में से महिलाओं की उम्र की तुलना करें। जो सबसे छोटी महिला है, उसको और उसके पति को सर्वेक्षण के लिए चुनें।	

Field	Question	Answer
57	Select the man's name from the list who will be interviewed. सूची में से उस आदमी का नाम चुनें, जिसका साक्षात्कार होगा।	
58	Select the woman's name from the list who will be interviewed. सूची में से उस औरत का नाम चुनें, जिसका साक्षात्कार होगा।	
59	Just to clarify: are [man_name] and [woman_name] husband and wife? सर्वेक्षणकर्ता, फिर से पुष्टि करने के लिए पूंछे: क्या [man_name] और [woman_name] पति और पत्नी हैं?	1 Yes हाँ 0 No नहीं
60	Enter the couple ID corresponding to [man_name] and [woman_name] from the household roster. [man_name] और [woman_name] के अनुरूप घर के रोस्टर में से जोड़ा/कपल आईडी दर्ज करें।	
Asset Ownership of the Household घर की संपत्ति का स्वामित्व		
note9	Please provide the following details about your household's asset ownership: कृपया अपनी घर की संपत्ति के बारे में निम्नलिखित विवरण प्रदान करें:	
61	Do you or anyone in the household possess box TV? क्या आप या आपके परिवार के किसी सदस्य के पास बॉक्स वाला टीवी है?	1 Yes हाँ 0 No नहीं
61a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
62	Do you or anyone in the household possess LCD/LED TV? क्या आप या आपके परिवार के किसी सदस्य के पास एलसीडी/एलेडी टीवी है?	1 Yes हाँ 0 No नहीं
62a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
63	Do you or anyone in the household possess fridge? क्या आप या आपके परिवार के किसी सदस्य के पास फ्रिज है?	1 Yes हाँ 0 No नहीं
63a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	

Field	Question	Answer
64	Do you or anyone in the household possess wall clock? क्या आप या आपके परिवार के किसी सदस्य के पास दीवार की घडी है?	1 Yes हाँ 0 No नहीं
64a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
65	Do you or anyone in the household possess LPG Gas stove? क्या आप या आपके परिवार के किसी सदस्य के पास एलपीजी गेस चूल्हा है?	1 Yes हाँ 0 No नहीं
65a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
66	Do you or anyone in the household possess cycle? क्या आप या आपके परिवार के किसी सदस्य के पास साइकल है?	1 Yes हाँ 0 No नहीं
66a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
67	Do you or anyone in the household possess scooter or bike? क्या आप या आपके परिवार के किसी सदस्य के पास स्कूटर/बाइक है?	1 Yes हाँ 0 No नहीं
67a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
68	Do you or anyone in the household possess car? क्या आप या आपके परिवार के किसी सदस्य के पास कार है?	1 Yes हाँ 0 No नहीं
68a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
69	Do you or anyone in the household possess a ceiling or a table fan? क्या आप या आपके परिवार के किसी सदस्य के पास पंखा (ceiling or table fan) है?	1 Yes हाँ 0 No नहीं
69a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	

Field	Question	Answer
70	Do you or anyone in the household possess cooler? क्या आप या आपके परिवार के किसी सदस्य के पास कूलर है?	1 Yes हाँ 0 No नहीं
70a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
71	Do you or anyone in the household possess AC? क्या आप या आपके परिवार के किसी सदस्य के पास वातानुकूलक (एर कंडिशनर) है?	1 Yes हाँ 0 No नहीं
71a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
72	Do you or anyone in the household possess computer/laptop? क्या आप या आपके परिवार के किसी सदस्य के पास कम्प्यूटर/लेपटोप है?	1 Yes हाँ 0 No नहीं
72a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
73	Do you or anyone in the household mobile with internet? क्या आप या आपके परिवार के किसी सदस्य के पास इंटरनेट वाला मोबाईल है?	1 Yes हाँ 0 No नहीं
73a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
73b	Who owns it? किनके पास है?	
74	Do you or anyone in the household mobile without internet? क्या आप या आपके परिवार के किसी सदस्य के पास मोबाईल बिना इंटरनेट का है?	1 Yes हाँ 0 No नहीं
74a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
75b	Who owns it? किनके पास है?	
76	Do you or anyone in the household possess sewing machine? क्या आप या आपके परिवार के किसी सदस्य के पास सिलाई मशीन है?	1 Yes हाँ 0 No नहीं
76a	How many do you or anyone in the household own? (enter total for all	

Field	Question	Answer
	members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में यह वस्तु है?	
77	Do you or anyone in the household possess land for farming in village? क्या आप या आपके परिवार के किसी सदस्य के पास गाँव में खुद की खेती वाली जमीन है?	1 Yes हाँ 0 No नहीं 999 Don't know/Cant say पता नहीं / बता नहीं सकते
77a	How much in acres do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी है एकर में है?	
78	Do you or anyone in the household possess rented land for farming in village? क्या आप या आपके परिवार के किसी सदस्य के पास गाँव में खेती के लिए ली गई किराए की जमीन है?	1 Yes हाँ 0 No नहीं 999 Don't know/Cant say पता नहीं / बता नहीं सकते
78a	How much in acres do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी है एकर में है?	
79	Do you or anyone in the household possess farm animals (eg. Cow, bullock, goat etc)? क्या आप या आपके परिवार के किसी सदस्य के पास खुद के खेत जानवर (जैसे गाय, बैल, बकरी आदि) है?	1 Yes हाँ 0 No नहीं 999 Don't know/Cant say पता नहीं / बता नहीं सकते
79a	How many do you or anyone in the household own? (enter total for all members) परिवार के सब सदस्यों का मिलाकर कितनी संख्या में है?	

Individual Survey

Field	Question	Answer
Basic Information > Respondent's Name सामान्य जानकारी > उत्तरदाता का नाम		
16	What is your full name? आपका पूरा नाम क्या है?	
16A	First Name प्रथम नाम	
16B	Last Name/Surname पारिवारिक नाम/कुल नाम	
17	Select the gender of the individual. व्यक्ति का लिंग चुनें	1 Male पुरुष 2 Female महिला
Basic Information > Respondent's Father's Name सामान्य जानकारी > उत्तरदाता के पिता का नाम		
18	What is your father's full name? आपके पिता का पूरा नाम क्या है?	
18A	First Name प्रथम नाम	
18B	Last Name/Surname पारिवारिक नाम/कुल नाम	
Basic Information > Respondent's Spouse's Name सामान्य जानकारी > उत्तरदाता के जीवन साथी का नाम		
19	What is your spouse's full name? आपके पति/पत्नी का पूरा नाम क्या है?	
19A	First Name प्रथम नाम	
19B	Last Name/Surname पारिवारिक नाम/कुल नाम	
20	Please note the spouse's ID from the household roster पति/पत्नी का घरेलू रोस्टर से ID नोट करें	
21	What is your jati? आपकी जाति क्या है?	
22	How old are you now? आप कितने साल के हो?	
Marital History वैवाहिक इतिहास		
23	How long have you been married? (in years) आपकी शादी को कितने साल हुए है? (सालो में)	
24	Do you have any children? क्या आपके कोई बच्चे हे?	1 Yes हाँ 0 No नहीं
children_note	Investigator,please ask the following questions on basic details about the children starting from the eldest. सर्वेक्षक, कृपया सबसे बड़े से लेकर छोटे बच्चे के बारे में आगे आने वाले बुनियादी सवाल उत्तरदाता से पूछें।	
Marital History > Please answer some basic details about your children starting from the eldest. (1) वैवाहिक इतिहास > कृपया अपने सबसे बड़े से लेकर छोटे बच्चे के बारे में कुछ बुनियादी विवरणों का उत्तर दें। (1)		(Repeated group)
25	Age of the child (in years, enter 0 for infants) बच्चे की आयु (सालों में, शिशु के लिए 0 दर्ज करें)	
26	Gender of the child बच्चे का लिंग	1 Male पुरुष

Field	Question	Answer
		2 Female महिला
27	Does he/she reside with you? क्या वह आपके साथ रहता/रहती है?	1 Yes हाँ 0 No नहीं
28	What is he/she currently doing? अभी वह क्या कर रहा/रही है?	1 Studying पढ़ाई 2 Working नौकरी/काम 3 Looking for work or unemployed काम की तलाश में या बेरोजगार 4 Too young to work or go to school पढ़ने या काम करने के लिए बहुत छोटा है 777 Other अन्य
29	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
Education अध्ययन		
30	What is the highest level of education you have achieved? आपने कहाँ तक पढ़ाई की है?	
31	Investigator, please ask the next questions from the respondent related to his/her educational qualifications. Add more rows if there are multiple degrees. सर्वेक्षक , कृपया उत्तरदाता से उसकी शिक्षा से संबंधित आगे आने वाले सवाल पूछें। एक से अधिक डिग्री के लिए टेबल में और पंक्तियाँ (Add row) जोड़ें।	
Education > Education Details (1)अध्ययन > शिक्षा डिग्री का विवरण (1)		(Repeated group)
32	Name of course/degree कोर्स का नाम / डिग्री	1 BA 2 B.Com 3 BS/BSc 4 BCA 5 BBA 6 B.Tech 7 MA 8 M.Com 9 MS/MSc 10 MCA 11 MBA 12 M.Tech 13 11th/12th Science 11th/12th साइंस

Field	Question	Answer
		14 11th/12th Commerce 11th/12th कॉमर्स 15 11th/12th Arts 11th/12th आर्ट्स 777 Other अन्य
33	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
34	Where was this degree completed from? यह डिग्री कहाँ से पूरी की गई थी?	1 School स्कूल 2 College कॉलेज 3 University यूनिवर्सिटी 4 Industrial Training Institute औद्योगिक प्रशिक्षण संस्थान (ITI) 5 Polytechnic पॉलिटेक्निक 777 Other अन्य
35	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
36	Name of the institution संस्थान का नाम	
37	Which state is the institution located in? संस्थान किस राज्य में स्थित है?	
38	Which city is the institution located in? संस्थान किस शहर में स्थित है?	
39	What is the type of institution? संस्थान का प्रकार	1 Private Institution प्राइवेट संस्थान 2 Public Institution सरकारी संस्थान 999 Don't know/ Cant say पता नही
40	What is the type of the course amongst the following? निम्नलिखित में से किस प्रकार का कोर्स है?	1 Regular रेगुलर 2 Correspondence कॉरेस्पोंडेंस (घर बैठे) 3 Part Time पार्ट टाइम
41	What was the duration of the course? (in years) कोर्स की अवधि (सालों में)	
42	Have you undertaken any other degree for example diploma or skill or technical training? क्या आपने कोई अन्य डिग्री हासिल करी है जैसे कि कोई कौशल या तकनीकी प्रशिक्षण या डिप्लोमा?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
note	Investigator, please ask the next questions from the respondent related to his/her skill	

Field	Question	Answer	
	or technical training. Add more rows if there are multiple degrees. सर्वेक्षक , कृपया उत्तरदाता से उसकी कौशल या तकनीकी प्रशिक्षण से संबंधित आगे आने वाले सवाल पूछें। एक से अधिक के लिए टेबल में और पंक्तियाँ (Add row) जोड़ें।		
Education > Skill details (1) अध्ययन > कौशल या तकनीकी प्रशिक्षण का विवरण (1)		(Repeated group)	
43	Name of the course/degree. कोर्स का नाम / डिग्री	1	Art (e.g. Painting, Music, Dance, Pottery, Craft etc) कला (जैसे कि चित्रकला, संगीत, नृत्य, मिट्टी के बर्तन बनाना, शिल्प आदि)
		2	Automobile (e.g. auto repair, mechanic) ऑटोमोबाइल (जैसे ऑटो मरंमत, मैकेनिक)
		3	Beauty and wellness (e.g. make-up, hair cutting, massage) ब्यूटी एंड वैलनेस (जैसे मेकअप, बाल काटना, मालिश)
		4	Civil (e.g. construction) सिविल (जैसे कि कंस्ट्रक्शन आदि)
		5	Computer कंप्यूटर
		6	Electrical इलेक्ट्रिकल
		7	Fashion Design फैशन डिजाइन
		8	Hospitality (e.g. chef course, hotel management) हॉस्पिटैलिटी (जैसे शेफ, होटल मैनेजमेंट)
		9	Garment (e.g. stitching, tailoring, embroidery) गारमेंट (जैसे कि सिलाई, कढ़ाई, बुनाई आदि)
		10	Information Technology इनफार्मेशन प्रौद्योगिकी/टेक्नोलॉजी

Field	Question	Answer
		11 Interior Design and Decoration इंटीरियर डिजाइन और सजावट 12 Library and Information Sciences पुस्तकालय और सूचना विज्ञान 13 Modern Office Practice (e.g. secretarial course)आधुनिक कार्यालय अभ्यास (जैसे कि सेक्रेटरी का कोर्स) 14 Pharmacy फार्मेसी 15 Sports/Yoga/Gym खेल/योगा/जिम ट्रेनर 16 Education (e.g. teacher certification) शिक्षा (जैसे कि शिक्षक सर्टिफिकेशन) 777 Other, अन्य
44	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
45	Where was this degree completed from? यह डिग्री कहाँ से पूरी की गई थी?	2 College कॉलेज 3 University यूनिवर्सिटी 4 Industrial Training Institute औद्योगिक प्रशिक्षण संस्थान (ITI) 5 Polytechnic पॉलिटेक्निक 777 Other अन्य
46	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
47	Which state is the institution located in? संस्थान किस राज्य में स्थित है?	
48	Which city is the institution located in? संस्थान किस शहर में स्थित है?	
49	What is the type of institution? संस्थान का प्रकार क्या है?	1 Private Institution प्राइवेट संस्थान 2 Public Institution सरकारी संस्थान 999 Don't know पता नही
50	What is the type of the course amongst the following? निम्नलिखित में से किस प्रकार का कोर्स है?	1 Regular रेगुलर 2 Correspondence कॉरेस्पोंडेंस (घर बैठे)

Field	Question	Answer
		3 Part time पार्ट टाइम
51	What was the duration of the course? (in months) कोर्स की अवधि (महीनों में)	
Mobile मोबाईल		
52	Do you use a mobile phone? क्या आप मोबाईल फोन इस्तमाल करते हो?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
53	Who owns the mobile phone you use? आप जो मोबाईल इस्तेमाल करते हो वो किसका है?	1 Self खुद का 2 Spouse पत्नी-पति का 3 Children बच्चे 4 Sibling भाई-बहन 5 Friend दोस्त 777 Other अन्य 888 Refuse to say उत्तर देने से मना किया
54	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
55	Can you provide us with the mobile number you use? क्या आप हमें आपके द्वारा उपयोग किए गए मोबाइल नंबर प्रदान कर सकते हैं?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
56	Please provide us with your mobile number. कृपया मोबाईल नम्बर दीजिए	
57	Do you send or receive text messages using a mobile phone? क्या आप मोबाइल फोन का उपयोग करके पाठ संदेश/टेक्स्ट मैसेज भेजते हैं या प्राप्त करते हैं?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
58	Do you have any social networking apps like whatsapp or facebook on your phone? आपके फोन में कोई सोशियल मिडिया जैसे की वोट्सअप या फेसबुक जैसी एप्स है?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
Native Home पैदाइश वाला घर (जन्म की जगह)		
59	Is Delhi your native home? क्या दिल्ली आपकी जन्म भूमि (पैतृक घर) है?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
60	Is your native home city or a village? आपकी जन्म भूमि शहर है या गॉव ?	1 City शहर 2 Village गॉव

Field	Question	Answer
		888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
61	What is the name of your native home? आपकी जन्म भूमि (पैतृक घर) का नाम क्या है?	
62	In what state is your native home? आपकी जन्म भूमि (पैतृक घर) किस राज्य में है?	
63	In what district is your native home? आपकी जन्म भूमि (पैतृक घर) कौन से जिल्ले में है?	
64	In what taluk/tehsil/sub-district is your native home? आपकी जन्म भूमि (पैतृकघर) कौन से तालुका/तहसील (थाना) में है?	
65	Do you visit your native home? क्या आप अपनी जन्म भूमि (पैतृक घर) जाते है?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
66	How often do you visit your native home? कितनी बार जातें हैं आप अपने पैतृक घर?	1 More than two times a year साल में दो बार से अधिक 2 Twice a year साल में दो बार 3 Once a year साल में एक बार 4 Once in two years 2 साल में एक बार 5 Once in three years 3 साल में एक बार 6 Once in five years 5 साल में एक बार 777 Other अन्य 888 Refuse to say उत्तर देने से मना किया
67	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
68	How long have you lived in Delhi? (In years) आप दिल्ली में कितने सालों से रह रहे हैं?	
	Next, please fill details related to the localities in Delhi the respondent has stayed in. अब कृपया प्रतिवादी द्वारा दिल्ली में रही हुई कॉलोनी/बस्तियों का विवरण भरें। (वर्तमान/नवीनतम कॉलोनी से शुरू करते हुए)	

Field	Question	Answer
Native Home > Please answer the following questions related to the localities in Delhi (starting with current) you have stayed in: (1) पैदाइश वाला घर (जन्म की जगह) > कृपया आप दिल्ली में रहे हुए अपनी बस्तियों से संबंधित आने वाले प्रश्नों के उत्तर दें : (1)		(Repeated group)
69	Name of your locality or colony कॉलोनी का नाम	
70	What is the duration of stay in this locality? (Record in years) इस कॉलोनी में रहेने की अवधि (सालों में रिकॉर्ड करें)	
71	Reason for moving to this locality इस कॉलोनी में आने का क्या कारण रहा?	1 Marriage शादी 2 Moved with family परिवार के साथ आ गए 3 For work काम के लिए 777 Other अन्य
72	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
73	Did anyone help your family move to this locality? इस जगह में आने के लिए क्या आप की किसी ने सहायता करी थी?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
74	Relationship with the person उनके साथ रिश्ता	1 SPOUSE पति या पत्नी 2 PARENT माता-पिता 3 UNCLE/AUNT चाचा/चाची/ताऊ/ ताई/ बुआ/ फूफा/मौसी/मौसा/मामा/मामी 4 SIBLING/COUSIN सगा भाई या बहन / कजिन 5 IN-LAWS ससुराल वाले 6 FRIEND मित्र 7 CO-WORKER सहकार्य कर्ता 8 NEIGHBOUR IN THE SAME LANE एक ही गली के पड़ोसी 9 NEIGHBOUR IN THE SAME BLOCK उसी ब्लॉक में पड़ोसी 10 NEIGHBOUR FROM PREVIOUS LOCALITY पुराने पडोसी

Field	Question	Answer
		11 NEIGHBOUR FROM NATIVE HOME पैदाइशी स्थान से पड़ोसी 777 OTHER अन्य 888 REFUSE TO SAY उत्तर देने से मना किया 999 DON'T KNOW पता नही
75	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
76	If not a relative, is this person same jati as you? अगर रिश्तेदार नही, तो क्या वह आपकी जाति का है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
77	Does this person currently live close to you? क्या वह अभी आप के नजदीक ही रहते हे?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
78	Are you still in touch with this person? क्या आप अभी भी उनसे संपर्क में है?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
79	How many times do you interact with this person in a typical month? महीने में कितनी बार आप उनसे मिलते हो?	1 More than four times a month महीने में चार बार से अधिक 2 Four times a month महीने में चार बार 3 Three times a month महीने में तीन बार 4 Twice a month महीने में दो बार 5 Once a month महीने में एक बार 6 Once in 6 monts छे महीने में एक बार 7 Once in a year एक साल में एक बार 8 Never कभी नहीं 777 Other अन्य

Field	Question	Answer	
80	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।		
81	How many times do you call/text this person in a typical month? महीने में कितनी बार आप उनसे फोन या मैसेज करते हो?		
82	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।		
Occupation and Previous Employment व्यवसाय और पिछला रोजगार			
83	What is your main occupation? (In terms of maximum time spent in last 12 months) आपका मुख्य व्यवसाय क्या है? (पिछले 12 महीनों में अधिकतम समय व्यतीत करने के संदर्भ में)	1	Wage labourer in factories मजदूरी (कारखानों/ फैक्ट्री में)
		2	Wage labourer in construction मजदूरी (कंस्ट्रक्शन/ बेलदारी में)
		3	Wage labourer in domestic work मजदूरी (घरों में सफाई/ खाना बनाने का काम)
		4	Casual Labour in other मजदूरी (अन्य)
		5	Self- employed in retail activities स्व-रोज़गार (रीटेल)
		6	Self- employed in own business manufacturing स्व-रोज़गार (उद्योग)
		7	Self- employed in other स्व-रोज़गार (अन्य)
		8	Salaried employee at non-govt (or private) नौकरी (गैर सरकारी)
		9	Salaried employee at government नौकरी (सरकारी)
		10	Housewife गृहिणी
		11	Unemployed बेरोजगार
		12	Student छात्र/छात्रा
		13	Cannot work due to disability/ ill-health

Field	Question	Answer
		विकलांगता / अस्वस्थता के कारण काम नहीं कर सकते 14 Retired रिटायर्ड (Retired) 777 Other अन्य
84	If other, please specify कृपया स्पष्ट करें।	
85	Are you working currently? क्या आप आज-कल में कोई काम कर रहे हैं?	1 Yes हाँ 0 No नहीं
Occupation and Previous Employment > Current Primary Work व्यवसाय और पिछला रोजगार > वर्तमान प्राथमिक नौकरी/काम		
current_note	Investigator, please ask the respondent the following questions related to his/her current job! सर्वेक्षक, उत्तरदाता की वर्तमान नौकरी से जुडे आगे आने वाले प्रश्न पूछें।	
86	Your position in this job इस नौकरी/काम में आपका रोल/पद	
87	For how long have you been doing this job? (Record the answer in months) आप कितने समय से यह काम कर रहे हैं? (महीनों में जवाब रिकॉर्ड करें)	
88	What is the type of your work? आपका कार्य का प्रकार क्या है?	1 Wage Employed तन्खा के लिए मजदूरी/नौकरी 2 Self Employed स्व नियोजित या खुद का काम 3 Wage saccording to Piece Rate टुकड़ा दर (पीस रेट) के अनुसार मजदूरी 777 Other अन्य
89	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
90	What is the type of the company? कंपनी का प्रकार क्या है ?	1 Small Enterprise लघु उद्योग 2 Medium Enterprise मध्यम उद्योग 3 Large Enterprise बड़े उद्योग 4 Retail छूटक/रिटेल 5 Services सेवाएं/सर्विसेज 6 Government सरकारी 7 NGO गैर सरकारी संगठन 777 Other अन्य

Field	Question	Answer
91	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
92	How many hours do/did you work in a day? आप एक दिन में कितने घंटे काम करते हैं ?	
93	How many days of a week do/did you work in this job? इस जॉब में आप हफ्ते के कितने दिन काम करते हैं ?	
94	How much do/did you earn monthly from this job on average? (INR) आप इस नौकरी/काम से महीने का औसतन कितना कमाते हैं? (INR)	
95	How did you get information about this work? आपको इस काम के बारे में जानकारी कैसे मिली?	1 Person व्यक्ति 2 Newspaper समाचार पत्र 3 Internet इंटरनेट 4 Job Fair जॉब फेयर 5 Skill training Program कौशल प्रशिक्षण कार्यक्रम 6 NGO एन जी ओ 7 SHG Group एस एच जी समूह 777 Other अन्य
96	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
97	Did this person also help you or refer you to the company or the employer? क्या इस व्यक्ति ने आपको नौकरी दिलाने में मदद भी की या कंपनी में आपको रेफर भी किया?	1 Yes हाँ 0 No नहीं
98	Did anyone help or refer you to the company/employer for this work? क्या इस काम के लिए किसी ने आपकी मदद की या कंपनी में रेफर (refer) किया?	1 Yes हाँ 0 No नहीं
99	Relationship with that person जिसने मदद की, उस व्यक्ति के साथ संबंध?	1 Spouse पति या पत्नी 2 Parent माता-पिता 3 Uncle/Aunt चाचा/चाची/ताऊ/ ताई/ बुआ/ फूफा/मौसी/मौसा/मामा/मामी 4 Sibling/Cousin सगा भाई या बहन / कजिन 5 In-laws ससुराल वाले 6 Friend मित्र 7 Coworker सहकार्य कर्ता

Field	Question	Answer
		8 Neighbour from the same lane एक ही गली के पड़ोसी 9 Neighbour from the same block उसी ब्लॉक में पड़ोसी 10 Neighbour from previous locality पुराने पडोसी 11 Neighbour from native home पैदाइशी स्थान से पड़ोसी 777 Other अन्य 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
100	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
101	Is this person same jati as you? क्या यह व्यक्ति आपके जाति का है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
102	How long have you known this person? (in months) आप इस व्यक्ति को कब से जानते हैं? (महीनों में)	
103	Does he/she work at the same place/ industry as you? क्या वह इसी इंडस्ट्री/उद्योग में काम करते हैं?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
104	Are you still in touch with that person? आप अभी भी उस व्यक्ति के संपर्क में हैं?	1 Yes हाँ 0 No नहीं
105	How many times do you interact with this person in a typical month? आप एक महीने में इस व्यक्ति के साथ कितनी बार मिलते हैं?	
106	If other, please specify.अन्य हैं, तो कृपया स्पष्ट करें।	
107	How many times do you call/text this person in a typical month? एक महीने में आप कितनी बार इस व्यक्ति को कॉल/ टेक्स्ट संदेसा करते हैं?	

Field	Question	Answer
108	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
109	Have you undertaken any primary work or full time job in the past two years? (Apart from the current work) क्या आपने पिछले दो वर्षों में कोई प्राथमिक कार्य या फुल-टाइम नौकरी की है? (वर्तमान नौकरी के अलावा)	1 Yes हाँ 0 No नहीं
pwork_note	Investigator, please ask the respondent the following questions related to his/her primary/full-time job(s)! सर्वेक्षक, उत्तरदाता की अन्य प्राथमिक/फुल-टाइम नौकरियों से जुडे आगे आने वाले प्रश्न पूछें। (वर्तमान नौकरी के अलावा और नवीनतम से शुरू करते हुए)	
Occupation and Previous Employment > Please describe all the primary/full-time jobs you have done in the past two years (except for your current job if you have one) व्यवसाय और पिछला रोजगार > कृपया उन सभी प्राथमिक/फुल-टाइम नौकरियों का वर्णन करें जो आपने पिछले दो वर्षों में की हों. (वर्तमान नौकरी के अलावा) (1)		(Repeated group)
110	Your position in this job इस नौकरी/काम में आपका रोल/पद	
111	For how many years did you do this work? (Record the answer in months) इस नौकरी/काम को आपने कितने साल किया? (महीनों में जवाब रिकॉर्ड करें)	
112	What is the type of your work? आपका कार्य का प्रकार क्या है?	
113	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
114	What is the type of the company? कंपनी का प्रकार क्या है ?	
115	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
116	How many hours do/did you work in a day? आप एक दिन में कितने घंटे काम करते थे ?	
117	How many days of a week do/did you work in this job? इस जॉब में आप हफ्ते के कितने दिन काम करते थे ?	
118	How much do/did you earn monthly from this job on average? (INR) आप इस नौकरी/काम से महीने का औसतन कितना कमाते थे ? (INR)	
119	How did you get information about this work? आपको इस काम के बारे में जानकारी कैसे मिली?	

Field	Question	Answer
120	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
121	Did this person also help you or refer you to the company or the employer? क्या इस व्यक्ति ने आपको नौकरी दिलाने में मदद भी की या कंपनी में आपको रेफर भी किया?	1 Yes हाँ 0 No नहीं
122	Did anyone help or refer you to the company/employer for this work? क्या इस काम के लिए किसी ने आपकी मदद की या कंपनी में रेफर (refer) किया?	1 Yes हाँ 0 No नहीं
123	Relationship with that person जिसने मदद की, उस व्यक्ति के साथ संबंध?	
124	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
125	Is this person same jati as you? क्या यह व्यक्ति आपके जाति का है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Dont know पता नही
126	How long have you known this person? (in months) आप इस व्यक्ति को कब से जानते हैं? (महीनों में)	
127	Does he/she work at the same place/ industry as you? क्या वह इसी इंडस्ट्री/उद्योग में काम करते हैं?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
128	Are you still in touch with that person? आप अभी भी उस व्यक्ति के संपर्क में हैं?	1 Yes हाँ 0 No नहीं
129	How many times do you interact with this person in a typical month? आप एक महीने में इस व्यक्ति के साथ कितनी बार मिलते हैं?	
130	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
131	How many times do you call/text this person in a typical month? एक महीने में आप कितनी बार इस व्यक्ति को कॉल/ टेक्स्ट संदेसा करते हैं?	
132	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
133	Reason for leaving this job यह नौकरी छोड़ने का कारण	1 Low Wages कम मजदूरी

Field	Question	Answer
		2 Family issue पारिवारिक मामला 3 Health issue स्वास्थय समस्या 4 Moved from the area खुद जगह से चले गए 5 Employer moved from the area नियोक्ता/मालिक क्षेत्र से चले गए 6 Exempted from the job नौकरी से छूट मिल गई 777 Other अन्य
134	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
135	Are you currently doing any part-time or secondary job? क्या आप आज-कल में कोई द्वितीय या पार्ट-टाइम नौकरी या काम कर रहे हो?	1 Yes हाँ 0 No नहीं
Occupation and Previous Employment > Current Secondary Work व्यवसाय और पिछला रोजगार > वर्तमान द्वितीय नौकरी/काम		
current_snote	Investigator, please ask the respondent the following questions related to his/her current secondary or part-time job! सर्वेक्षक, उत्तरदाता की वर्तमान द्वितीय या पार्ट-टाइम नौकरी से जुडे आगे आने वाले प्रश्न पूछें।	
136	Your position in this job इस नौकरी/काम में आपका रोल/पद	
137	For how long have you been doing this job? (Record the answer in months) आप कितने समय से यह काम कर रहे हैं? (महीनों में जवाब रिकॉर्ड करें)	
138	What is the type of your work? आपका कार्य का प्रकार क्या है?	
139	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
140	What is the type of the company? कंपनी का प्रकार क्या है ?	
141	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
142	How many hours do/did you work in a day? आप एक दिन में कितने घंटे काम करते हैं ?	
143	How many days of a week do/did you work in this job? इस जॉब में आप हफ्ते के कितने दिन काम करते हैं ?	

Field	Question	Answer
144	How much do/did you earn monthly from this job on average? (INR) आप इस नौकरी/काम से महीने का औसतन कितना कमाते हैं ? (INR)	
145	How did you get information about this work? आपको इस काम के बारे में जानकारी कैसे मिली?	
146	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
147	Did this person also help you or refer you to the company or the employer? क्या इस व्यक्ति ने आपको नौकरी दिलाने में मदद भी की या कंपनी में आपको रेफर भी किया?	1 Yes हाँ 0 No नहीं
148	Did anyone help or refer you to the company/employer for this work? क्या इस काम के लिए किसी ने आपकी मदद की या कंपनी में रेफर (refer) किया?	1 Yes हाँ 0 No नहीं
149	Relationship with that person जिसने मदद की, उस व्यक्ति के साथ संबंध?	
150	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
151	Is this person same jati as you? क्या यह व्यक्ति आपके जाति का है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
152	How long have you known this person? (in months) आप इस व्यक्ति को कब से जानते हैं? (महीनों में)	
153	Does he/she work at the same place/ industry as you? क्या वह इसी इंडस्ट्री/उद्योग में काम करते हैं?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
154	Are you still in touch with that person? आप अभी भी उस व्यक्ति के संपर्क में हैं?	1 Yes हाँ 0 No नहीं
155	How many times do you interact with this person in a typical month? आप एक महीने में इस व्यक्ति के साथ कितनी बार मिलते हैं?	
156	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	

Field	Question	Answer
157	How many times do you call/text this person in a typical month? एक महीने में आप कितनी बार इस व्यक्ति को कॉल/ टेक्स्ट संदेसा करते हैं?	
158	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
159	Have you undertaken any other secondary work or part-time job in the past two years? क्या आपने पिछले दो वर्षों में कोई अन्य द्रितीय कार्य या पार्ट-टाइम नौकरी की है?	1 Yes हाँ 0 No नहीं
swork_note	Investigator, please ask the respondent the following questions related to his/her secondary or part-time job(s)! सर्वेक्षक, उत्तरदाता की अन्य द्वितीय या पार्ट-टाइम नौकरियों से जुडे आगे आने वाले प्रश्न पूछें। (वर्तमान के अलावा और नवीनतम से शुरू करते हुए)	
Occupation and Previous Employment > Please describe all the secondary/part-time jobs you have done in the past two years (appart from any current job). (1) व्यवसाय और पिछला रोजगार > कृपया अन्य द्रितीय/पार्ट-टाइम नौकरियों का वर्णन करें जो आपने पिछले दो वर्षों में की हों (किसी वर्तमान कार्य के अलावा) (1)		(Repeated group)
160	Your position in this job इस नौकरी/काम में आपका रोल/पद	
161	For how many years did you do this work? (Record the answer in months) इस नौकरी/काम को आपने कितने साल किया? (महीनों में जवाब रिकॉर्ड करें)	
162	What is the type of your work? आपका कार्य का प्रकार क्या है?	
163	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
164	What is the type of your company? कंपनी का प्रकार क्या है ?	
165	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
166	How many hours do/did you work in a day? आप एक दिन में कितने घंटे काम करते थे ?	
167	How many days of a week do/did you work in this job? इस जॉब में आप हफ्ते के कितने दिन काम करते थे ?	
168	How much do/did you earn monthly from this job on average? (INR) आप इस नौकरी/काम से महीने का औसतन कितना कमाते थे ? (INR)	

Field	Question	Answer
169	How did you get information about this work? आपको इस काम के बारे में जानकारी कैसे मिली?	
170	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
171	Did this person also help you or refer you to the company or the employer? क्या इस व्यक्ति ने आपको नौकरी दिलाने में मदद भी की या कंपनी में आपको रेफर भी किया?	1 Yes हाँ 0 No नहीं
172	Did anyone help or refer you to the company/employer for this work? क्या इस काम के लिए किसी ने आपकी मदद की या कंपनी में रेफर (refer) किया?	1 Yes हाँ 0 No नहीं
173	Relationship with that person जिसने मदद की, उस व्यक्ति के साथ संबंध?	
174	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
175	Is this person same jati as you? क्या यह व्यक्ति आपके जाति का है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
176	How long have you known this person? (in months) आप इस व्यक्ति को कब से जानते हैं? (महीनों में)	
177	Does he/she work at the same place/ industry as you? क्या वह इसी इंडस्ट्री/उद्योग में काम करते हैं?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
178	Are you still in touch with that person? आप अभी भी उस व्यक्ति के संपर्क में हैं?	1 Yes हाँ 0 No नहीं
179	How many times do you interact with this person in a typical month? आप एक महीने में इस व्यक्ति के साथ कितनी बार मिलते हैं?	
180	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
181	How many times do you call/text this person in a typical month? एक महीने में आप कितनी बार इस व्यक्ति को कॉल/ टेक्स्ट संदेसा करते हैं?	
182	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	

Field	Question	Answer
Network नेटवर्क		
note1a	Investigator: Ask the respondent to name people not currently residing with them that they most often interact with on the following activities: सर्वेक्षक : प्रतिवादी से उन लोगों के नाम पूछें जो वर्तमान में उनके साथ नहीं रहते और जिनके साथ वे निम्नलिखित गतिविधियाँ करते हैं:	
note1b	(In case of emergency) Investigator please tell the respondent: "Now we will pose some emergency situations in front of you. Please tell us who would you take help from in those situations except for the people residing at your house." (आपात्कालीन स्थिति में) सर्वेक्षक, कृपया उत्तरदाता से बोलें : "अब हम आपके सामने कुछ एमर्जेन्सी/emergency (आपातकालीन) स्थितियाँ रखेंगे। कृपया आप हमें बताइए कि उन स्थितियों में आपके घर में रहने वाले लोगों के अलावा आप किससे मदद लेते हैं।"	
Network > In case of emergency1 (1) नेटवर्क > आपात्कालीन स्थिति में 1 (1)		(Repeated group)
183	Borrowing from in case of emergency; for example if you immediately need 400-500 rupees for a day and there is no one else at home you could borrow from? एमर्जेन्सी (emergency) में उधार पैसे या हथ फेर लेना; उदाहरण के लिए अगर आपको तुरंत एक दिन के लिए 400-500 रुपये चाहिए और घर पर कोई और नहीं है, तो आप किससे उधार लेंगे?	2 PARENT माता-पिता 3 UNCLE/AUNT चाचा/चाची/ताऊ/ ताई/ बुआ/ फूफा/मौसी/मौसा/मामा/मामी 4 SIBLING/COUSIN सगा भाई या बहन / कजिन 5 IN-LAWS ससुराल वाले 6 FRIEND मित्र 7 COWORKER सहकार्य कर्ता 8 NEIGHBOUR FROM THE SAME LANE एक ही गली के पड़ोसी 9 NEIGHBOUR FROM THE SAME BLOCK उसी ब्लॉक में पड़ोसी 10 NEIGHBOUR FROM PREVIOUS LOCALITY पुराने पड़ोसी 11 NEIGHBOUR FROM NATIVE HOME पैदाइशी स्थान से पड़ोसी 12 NONE कोई नहीं

Field	Question	Answer
		777 OTHER अन्य 888 REFUSE TO SAY उत्तर देने से मना किया
183a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
184	Enter Name उनका नाम बताइए।	
note_network1	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you would take help from in this emergency situation?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें: "क्या आप इस एमर्जेन्सी (आपातकालीन) स्थिति में और किसी से मदद ले सकते हैं? कृपया आप सोच के बता सकते हैं ?"	
Network > In case of emergency1 (2) नेटवर्क > आपात्कालीन स्थिति में 1 (2)		(Repeated group)
185	Borrowing from in case of emergency; for example if you immediately need 400-500 rupees for a day and there is no one else at home you could borrow from? एमर्जेन्सी (emergency) में उधार पैसे या हथ फेर लेना; उदाहरण के लिए अगर आपको तुरंत एक दिन के लिए 400-500 रुपये चाहिए और घर पर कोई और नहीं है, तो आप किससे उधार लेंगे?	
185a	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
186	Enter Name उनका नाम बताइए।	
note2a	Investigator, for the next situation please try to get different names apart from the ones already entered in the previous situation. If the respondent doesn't take new names, please fill the same names entered previously. सर्वेक्षक, अगली स्थिति के लिए कृपया नए लोगों के बारें में पूछें जिनका पहले नाम नहीं लिया गया है । यदि प्रतिवादी नए नाम नहीं लेता है, कृपया पिछले वाले नामों को ही दर्ज करें जिनसे वह इस स्थिति में मदद लेता है।	
note2b	Investigator, please tell the respondent: "We will now ask about the second emergency situation. Please tell us who do you take help from in this situation. Please name	

Field	Question	Answer
	anyone apart from the ones you have named already." सर्वेक्षक, कृपया उत्तरदाता से कहें : "अब हम दूसरी एमर्जेन्सी (आपातकालीन) स्थिति के बारे में पूछेंगे । हमें बताएं कि आप इस स्थिति में किस से मदद लेते हैं । कृपया पहले जो नाम लिए जा चुकें हैं उनके अलावा कोई और लोग सोचें और बताइये।"	
Network > In case of emergency2 (1) नेटवर्क > आपात्कालीन स्थिति में 2 (1)		(Repeated group)
187	In case of medical emergency when you need to call someone immediately to rush to the doctor/hospital and there is no one else at home मेडिकल एमर्जेन्सी (तत्कालीन स्थिति) में जब आपको तुरंत डॉक्टर / अस्पताल जाने के लिए किसी को फोन करना या बुलाना पड़े और घर पर कोई न हो, तब किस से मदद माँगेंगे?	
187a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
188	Enter Name उनका नाम बताइए।	
note_network2	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you would take help from in this emergency situation?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें : "क्या आप इस एमर्जेन्सी (आपातकालीन) स्थिति में और किसी से मदद ले सकते हैं? कृपया आप सोच के बता सकते हैं ?"	
Network > In case of emergency2 (2) नेटवर्क > आपात्कालीन स्थिति में 2 (2)		(Repeated group)
189	In case of medical emergency when you need to call someone immediately to rush to the doctor/hospital and there is no one else at home मेडिकल एमर्जेन्सी (तत्कालीन स्थिति) में जब आपको तुरंत डॉक्टर / अस्पताल जाने के लिए किसी को फोन करना या बुलाना पड़े और घर पर कोई न हो, तब किस से मदद माँगेंगे?	
189a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
190	Enter Name उनका नाम बताइए।	
note3a	Investigator, for the next situation please try to get different names apart from the ones	

Field	Question	Answer
	already entered in the previous two situations. If the respondent doesn’t take new names, please fill the same names entered previously. सर्वेक्षक, अगली स्थिति के लिए कृपया नए लोगों के बारें में पूछें जिनका पहले नाम नहीं लिया गया है । यदि प्रतिवादी नए नाम नहीं लेता है, कृपया पिछले वाले नामों को ही दर्ज करें जिनसे वह इस स्थिति में मदद लेता है।	
note3b	Investigator, please tell the respondent: "We will now ask about the third and last emergency situation. Please tell us who do you take help from in this situation. Please name anyone apart from the ones you have named already." सर्वेक्षक, कृपया उत्तरदाता से कहें : "अब हम तीसरी और आखिरी एमर्जेन्सी (आपातकालीन) स्थिति के बारे में पूछेंगे । हमें बताएं कि आप इस स्थिति में किससे मदद लेते हैं । कृपया पहले जो नाम लिए जा चुकें हैं उनके अलावा कोई और लोग सोचें और बताइये।"	
Network > In case of emergency3 (1) नेटवर्क > आपात्कालीन स्थिति में 3 (1)		(Repeated group)
191	In your neighbourhood if you have to immediately borrow food items like rice, tea, sugar, cooking fuel etc, who would you go to? आपके पड़ोस में अगर आपको चावल, चाय, चीनी, खाना पकाने के लिए गैस आदि जैसे खाद्य पदार्थों को तुरंत उधार लेना पड़े तो आप किसके पास जाएँगे ?	
191a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
192	Enter Name उनका नाम बताइए।	
note_network3	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you would take help from in this emergency situation?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें : "क्या आप इस एमर्जेन्सी (आपातकालीन) स्थिति में और किसी से मदद ले सकते हैं? कृपया आप सोच के बता सकते हैं ?"	
Network > In case of emergency3 (2) नेटवर्क > आपात्कालीन स्थिति में 3 (2)		(Repeated group)
193	In your neighbourhood if you have to immediately borrow food items like rice, tea,	

Field	Question	Answer
	sugar, cooking fuel etc, who would you go to? आपके पड़ोस में अगर आपको चावल, चाय, चीनी, खाना पकाने के लिए गैस आदि जैसे खाद्य पदार्थों को तुरंत उधार लेना पड़े तो आप किसके पास जाएँगे ?	
193a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
194	Enter Name उनका नाम बताइए।	
note4a	Investigator, for the next situation please try to get different names apart from the ones already entered in the previous situations. If the respondent doesn't take new names, please fill the same names entered previously. सर्वेक्षक, अगली स्थिति के लिए कृपया नए लोगों के बारें में पूछें जिनका पहले नाम नहीं लिया गया है । यदि प्रतिवादी नए नाम नहीं लेता है, कृपया पिछले वाले नामों को ही दर्ज करें जिनके साथ वह इस गतिविधि को करता है।	
note4b	(Around Home) Investigator, please tell the respondent: "We will now present some social activities to you. Please tell us who you do that activity with except for the people residing at your home. Kindly think of new people who you havent mentioned before." (घर के आसपास) : सर्वेक्षक, कृपया उत्तरदाता से बोलें : "अब हम आपके सामने कुछ सोशल एक्टिविटी/activity (गतिविधियाँ) रखेंगे। कृपया आप हमें बताइए कि आपके घर में रहने वाले लोगों के अलावा आप किसके साथ वह एक्टिविटी/गतिविधि में हिस्सा लेते हैं। कृपया नए लोगों के बारें में बताएं जिनका आपने अब तक ज़िक्र ना किया हो।"	
Network > Around Home1 (1) नेटवर्क > घर के आसपास 1 (1)		(Repeated group)
195	Going for a walk/to the park and chatting with in free time आप किसके साथ खाली समय बिताते हैं जैसे कि फ्री टाइम में बातें करना, दिल की बातें शेयर करना, पार्क में टहलने जाना या वाक पे जाना आदि?	
195a	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
196	Enter Name उनका नाम बताइए।	

Field	Question	Answer
note_network4	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you go to park or walk with?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें : "क्या आप इनके अलावा और किसी के साथ खाली समय बिताते हैं या वाक या टहलने जातें हैं? कृपया आप सोच के बता सकते हैं ? "	
Network > Around Home1 (2)	नेटवर्क > घर के आसपास 1 (2)	(Repeated group)
197	Going for a walk/to the park and chatting with in free time आप किसके साथ खाली समय बिताते हैं जैसे कि फ्री टाइम में बातें करना, दिल की बातें शेयर करना, पार्क में टहलने जाना या वाक पे जाना आदि?	
197a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
198	Enter Name उनका नाम बताइए।	
note5a	Investigator, for the next situation please try to get different names apart from the ones already entered in the previous situations. If the respondent doesn't take new names, please fill the same names entered previously. सर्वेक्षक, अगली गतिविधि के लिए कृपया नए लोगों के बारें में पूछें जिनका पहले नाम नहीं लिया गया है । यदि प्रतिवादी नए नाम नहीं लेता है, कृपया पिछले वाले नामों को ही दर्ज करें जिनके साथ वह इस गतिविधि को करता है।	
note5b	Investigator, please tell the respondent: "We will now ask about the second social activity. Please tell us who do you do this activity with. Please name anyone apart from the ones you have named already." सर्वेक्षक, कृपया उत्तरदाता से कहें : "अब हम दूसरी सोशल एक्टिविटी (activity)/गतिविधि के बारे में पूछेंगे । हमें बताएं कि आप यह activity/गतिविधि किसके साथ करते हैं । कृपया पहले जो नाम लिए जा चुकें हैं उनके अलावा कोई और लोग सोचें और बताइये।"	
Network > Around Home2 (1)	नेटवर्क > घर के आसपास 2 (1)	(Repeated group)
199	Shopping or going to local market with, for example to buy vegetables or ration?	

Field	Question	Answer
	खरीदारी करने के लिए बाजार में साथ जाना हो, उदाहरण के लिए सब्जियां या राशन खरीदना या फिर पर्सनल शॉपिंग करना, तो किसके साथ जाते हैं?	
199a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
200	Enter Name उनका नाम बताइए।	
note_network5	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you go shopping with?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें : "क्या आप इनके अलावा और किसी के साथ शॉपिंग (shopping) पे जातें हैं? कृपया आप सोच के बता सकते हैं ? "	
Network > Around Home2 (2) नेटवर्क > घर के आसपास 2 (2)		(Repeated group)
201	Shopping or going to local market with, for example to buy vegetables or ration? खरीदारी करने के लिए बाजार में साथ जाना हो, उदाहरण के लिए सब्जियां या राशन खरीदना या फिर पर्सनल शॉपिंग करना, तो किसके साथ जाते हैं?	
201a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
202	Enter Name उनका नाम बताइए।	
note6a	Investigator, for the next situation please try to get different names apart from the ones already entered in the previous situations. If the respondent doesn't take new names, please fill the same names entered previously.सर्वेक्षक, अगली गतिविधि के लिए कृपया नए लोगों के बारे में पूछें जिनका पहले नाम नहीं लिया गया है । यदि प्रतिवादी नए नाम नहीं लेता है, कृपया पिछले वाले नामों को ही दर्ज करें जिनके साथ वह इस गतिविधि को करता है।	
note6b	Investigator, please tell the respondent: "We will now ask about the third and last social activity. Please tell us who do you do this activity with. Please name anyone apart from the ones you have named already."सर्वेक्षक, कृपया उत्तरदाता से कहें : "अब हम तीसरी और आखिरी सोशल एक्टिविटी/गतिविधि के बारे में पूछेंगे । हमें बताएं कि आप यह activity/गतिविधि किसके साथ करते हैं । कृपया पहले जो नाम लिए जा चुकें हैं उनके अलावा कोई और लोग सोचें और बताइये।"	

Field	Question	Answer
Network > Around Home3 (1) नेटवर्क > घर के आसपास 3 (1)		(Repeated group)
203	Attending social functions or festivals or going to religious places with; for example going to the temple/mosque or participating in group pooja/prayer in the colony or meeting during Diwali or Chhat Puja celebrations etc? सामाजिक कार्यों या उत्सवों में भाग लेना हो या धार्मिक स्थानों पर साथ जाना हो तो किसके साथ जाते हैं; जैसे मंदिर / मस्जिद में जाना या कॉलोनी में किसी सामूहिक प्रार्थना या सत्संग में भाग लेना या दीवाली या छठ पूजा समारोह आदि के दौरान मिलना, तो किस से मिलते हैं और त्यौहार मनाते हैं? पूजा के अलावा शादी-व्याह में जाना हो तो किसके साथ जाते हैं?	
203a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
204	Enter Name. उनका नाम बताइए।	
note_network6	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you attend social functions with?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें: "क्या आप इनके अलावा और किसी के साथ सामूहिक उत्सवों या कार्यक्रम या पूजा में जाते हैं? कृपया आप सोच के बता सकते हैं?"	
Network > Around Home3 (2) नेटवर्क > घर के आसपास 3 (2)		(Repeated group)
205	Attending social functions or festivals or going to religious places with; for example going to the temple/mosque or participating in group pooja/prayer in the colony or meeting during Diwali or Chhat Puja celebrations etc? सामाजिक कार्यों या उत्सवों में भाग लेना हो या धार्मिक स्थानों पर साथ जाना हो तो किसके साथ जाते हैं; जैसे मंदिर / मस्जिद में जाना या कॉलोनी में किसी सामूहिक प्रार्थना या सत्संग में भाग लेना या दीवाली या छठ पूजा समारोह आदि के दौरान मिलना, तो किस से मिलते हैं और त्यौहार मनाते हैं? पूजा के अलावा शादी-व्याह में जाना हो तो किसके साथ जाते हैं?	
205a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	

Field	Question	Answer
206	Enter Name. उनका नाम बताइए।	
note7a	Investigator, the next two situations are work related. Please make sure to get names of co-workers which are not same as the ones already entered in the previous situations. If the respondent doesn't take new names, please fill the same names entered previously who he does the following activities with. Select "Not Applicable" if the respondent is not working currently. सर्वेक्षक, अगली दो स्थितियां काम से संबंधित हैं। कृपया सहकर्मियों के नाम प्राप्त करें जो पिछली स्थितियों में पहले दर्ज नहीं किए गए हैं। यदि प्रतिवादी नया नाम नहीं लेता है, तो कृपया पहले दर्ज किए गए नाम भरें जिनके साथ वह निम्नलिखित गतिविधियों करता है। अगर प्रतिवादी कोई जॉब या काम नहीं करता है तो आप "लागू नहीं" चुनें और आगे बढ़ें।	
note7b	(Around Work) Investigator, please tell the respondent if he/she is currently working: "We will now present some activities to you conducted during work. Please tell us who you do that activity with which should ideally be your coworkers. Kindly think of new people who you havent mentioned before." (काम की जगह के आसपास): सर्वेक्षक, यदि प्रतिवादी वर्तमान में काम कर रहा है, तो कृपया उससे कहें: "हम अब आपके सामने कुछ स्थितियाँ प्रस्तुत करेंगे जो काम के दौरान करी जाती हैं। कृपया हमें बताएं कि आप वह activity/गतिविधि किसके साथ करते हैं, जो कि आदर्श रूप से आपके साथ काम करने वाला (colleague) होना चाहिए। कृपया नए लोगों के बारें में सोचें जिनका आपने पहले ज़िक्र नहीं किया है। "	
Network > Around Workplace1 (1) नेटवर्क > काम की जगह 1 (1)		(Repeated group)
207	Having lunch at work or spending your free time at work with; for example chatting or having tea while taking a break काम पर दोपहर का खाना किसके साथ खातें हैं या फिर काम पर खाली वक्त हो तब, गपशप या ब्रेक के समय में साथ में चाय किसके साथ पीते हैं ?	
207a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
208	Enter Name उनका नाम बताइए।	
note_network7		

Field	Question	Answer
	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you spend time eating or gossiping at work with?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें : "क्या आप कोई और सहकर्मी (colleague) या मित्र बता सकते हैं, जिनके साथ आप काम की जगह पे खाना खाते हो या चाय पीते हो और गपशप करते हो?"	
Network > Around Workplace1 (2) नेटवर्क > काम की जगह 1 (2)		(Repeated group)
209	Having lunch at work or spending your free time at work with; for example chatting or having tea while taking a break काम पर दोपहर का खाना किसके साथ खातें हैं या फिर काम पर खाली वक्त हो तब, गपशप या ब्रेक के समय में साथ में चाय किसके साथ पीते हैं ?	
209a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
210	Enter Name उनका नाम बताइए।	
note8a	Investigator, for the next work situation please try to get different names apart from the ones already entered in the previous situation. If the respondent doesn't take new names, please fill the same names entered previously. सर्वेक्षक, अगली काम सम्बंधित स्थिति के लिए, कृपया पिछली स्थिति से अलग नाम प्राप्त करने का प्रयास करें। यदि उत्तरदाता नया नाम नहीं लेता है, तो कृपया पहले दर्ज किए गए नाम भरें जिसके साथ वह यह गतिविधि करता है।	
note8b	Investigator, please tell the respondent: "We will now ask about the last work related activity. Please tell us who do you do this activity with. Please name anyone apart from the ones you have named already."सर्वेक्षक, कृपया प्रतिवादी को बताएं: "हम अब काम से सम्बंधित अंतिम activity/गतिविधि के बारे में पूछेंगे। कृपया हमें बताएं कि आप इस गतिविधि को किसके साथ करते हैं। कृपया जिन लोगों का नाम आपने पहले से लिया है, उनके अलावा कोई और नाम सोचें और बताएं।"	
Network > Around Workplace2 (1) नेटवर्क > काम की जगह 2 (1)		(Repeated group)

Field	Question	Answer
211	Travelling to work with साथ में काम पे जाना हो तो किसके साथ जाते हैं?	
211a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
212	Enter Name उनका नाम बताइए।	
note_network8	Investigator, please prompt the respondent to think of more names and ask them "Can you think of and name more people who you travel to work with?" सर्वेक्षक, उत्तरदाता से और व्यक्तियों के बारे में सोचने के लिए कहें और उनसे पूछें : "क्या आप कोई और सहकर्मी (colleague) या मित्र बता सकते हैं, जिनके साथ आप काम की जगह पे जाते हैं?"	
Network > Around Workplace2 (2) नेटवर्क > काम की जगह 2 (2)		(Repeated group)
213	Travelling to work with साथ में काम पे जाना हो तो किसके साथ जाते हैं?	
213a	If other, please specify. अन्य हैं, तो कृपया स्पष्ट करें।	
214	Enter Name उनका नाम बताइए।	
List of people in the network नेटवर्क में लोगों की सूची		
note11	Investigator, the next question will require the respondent to rank the people he/she has named in order of the closeness with that person. Please select one-by-one from the list each name in order of decreasing closeness of the person with the respondent i.e. the most closest person will be selected first and the least closest will be selected in the end. Do not select the same name more than once. सर्वेक्षक, अगले प्रश्न में प्रतिवादी से निकटता घटने के क्रम में लोगों को रैंक कराया जाएगा जिसका उसने अब तक नाम लिया। कृपया सूची में से करीबी/निकटता घटने के क्रम में व्यक्ति के नाम चुनें, यानी सबसे निकटतम व्यक्ति को पहले चुना जाएगा और सबसे कम निकटतम को अंत में चुना जाएगा। किसी नाम का एक से अधिक बार चयन ना करें।	
note_network	Investigator, the names entered by you are " [name1] , [name2] , [name3], [name4] , [name5] , [name6] , [name7] , [name8] , [name9] , [name10] , [name11] , [name12] , [name13] , [name14] , [name15] and	

Field	Question	Answer
	[name16]". Please confirm the unique names with the respondent. सर्वेक्षक, आपके द्वारा दर्ज किए गए नाम है : " [name1] , [name2] , [name3] , [name4] , [name5] , [name6], [name7], [name8], [name9] , [name10] , [name11] , [name12] , [name13] , [name14] , [name15] और [name16] " | कृपया इनमें से अद्वितीय नामों का प्रतिवादी के साथ पुष्टि करें।	
List of people in the network > Names of people in the Social Network (1) नेटवर्क में लोगों की सूची > सोशल नेटवर्क में लोगों के नाम (1)		(Repeated group)
215	Network ID नेटवर्क ID	
note_socialnetwork	Investigator, ask for the closest person amongst the list excluding the name(s) already entered in the table. सर्वेक्षक, टेबल में पहले से दर्ज किए गए नाम (नामों) को छोड़कर निकटतम (सबसे करीबी) व्यक्ति के लिए पूछें।	
216	Out of these people who are you closest to? इनमें से आपके सबसे करीबी कौन हैं?	${name1} ... ${name2} ... ${name3} ... ${name4} ... ${name5} ... ${name6} ... ${name7} ... ${name8} ... ${name9} ... ${name10} ... ${name11} ... ${name12} ... ${name13} ... ${name14} ... ${name15} ... ${name16} ...
Nature of Relationship रिश्ते की प्रकृति		
instruction1	The following questions needs to be asked for each of the people named previously. Select a person's name and then ask the following questions for that person. Repeat the process for each person. निम्नलिखित प्रश्न पहले नाम लिए गए व्यक्तियों के लिए पूछे जाएंगे । एक व्यक्ति के नाम का चयन करें	

Field	Question	Answer
	और फिर उस व्यक्ति के लिए आगे आने वाले प्रश्न पूछें। प्रत्येक व्यक्ति के लिए इस प्रक्रिया को दोहराएं।	
Nature of Relationship > Nature of Relationship (1) रिश्ते की प्रकृति > रिश्ते की प्रकृति (1)		(Repeated group)
217	Select name of the person व्यक्ति के नाम को चुनें	1 ... 2 ... 3 ... 4 ... 5 ... 6 ... 7 ... 8 ...
218	How long have you known [nature_person_name] ? (in months) (If a relative, enter 666) [nature_person_name] को आप कब से जानते हैं? (महीनों में) (रिश्तेदारों के लिए 666 लिखें)	
219	Is [nature_person_name] from the same jati as you? (If a relative, select 'Not Applicable') क्या [nature_person_name] आपके ही जाति के है? (रिश्तेदारों के लिए 'लागू नहीं')	1 Yes हा 0 No नही 666 Not Applicable लागू नहीं 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
220	How did you get to know [nature_person_name]? (If a relative, select 'Not Applicable') आपकी [nature_person_name] से कैसे मुलाकात हुई ? (रिश्तेदारों के लिए 'लागू नहीं')	1 Coworker from previous work पिछले काम से सहकर्मी 2 Coworker from current work वर्तमान कार्य से सहकर्मी 3 Live in the same lane उसी गली में रहते हैं 4 Live in the same block उसी ब्लॉक में रहते हैं 5 Lived in the same previous locality पुराने पडोसी 6 Mutual friend किसी अन्य दोस्त के ज़रिये

Field	Question	Answer
		7 Neighbour from same native home पैदाइशी स्थान से पड़ोसी 777 Other अन्य 666 Not applicable लागू नहीं 888 Refuse to say उत्तर देने से मना किया
221	If other, please specify. Otherwise enter 666. अन्य हैं, तो कृपया स्पष्ट करें। अन्यथा 666 दर्ज करें।	
222	Is [nature_person_name] in any of your whatsapp or facebook groups? क्या [nature_person_name] आप के किसी व्हाट्सएप या फेसबुक ग्रुप में है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
223	Does [nature_person_name] work currently? क्या [nature_person_name] वर्तमान में काम करते है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
224	What is [nature_person_name] 's main occupation? [nature_person_name] का मुख्य व्यवसाय क्या है?	
225	If other, please specify. कृपया स्पष्ट करें।	
226	What is [nature_person_name] 's marital status? [nature_person_name] की वैवाहिक स्थिति क्या है?	
227	Does [nature_person_name]'s spouse work currently? क्या [nature_person_name] का/की पति/पत्नी वर्तमान में काम करता/करती है?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
228	What is the spouse's main occupation? पति या पत्नी का मुख्य व्यवसाय क्या है?	
229	If other, please specify. कृपया स्पष्ट करें।	
230	Can you provide us with [nature_person_name]'s address? क्या आप हमें [nature_person_name] का पता प्रदान कर सकते हैं?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही

Field	Question	Answer
Nature of Relationship > Nature of Relationship (1) > Person's Address रिश्ते की प्रकृति > रिश्ते की प्रकृति (1) > व्यक्ति का पता		
231	Please provide us with the full address of the person. कृपया हमें व्यक्ति का पूरा पता प्रदान करें।	
231A	Name of the Block. ब्लॉक का नाम	
231B	House number घर का नंबर	
231C	Floor Number फ्लोर नंबर	
231D	Name of the colony. कॉलोनी का नाम	
232	Can you provide us with [nature_person_name]'s mobile number? क्या आप हमें [nature_person_name] का फ़ोन नंबर प्रदान कर सकते हैं?	1 Yes हा 0 No नही 666 Not Applicable लागू नहीं 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
233	Please note down [nature_person_name]'s mobile number. कृपया [nature_person_name] का मोबाइल नंबर नोट करें।	
Intensity of Relationship रिश्ते की तीव्रता		
instruction2	The following questions needs to be asked for each of the people named previously. Select a person's name and then ask the following questions for that person. Repeat the process for each person. निम्नलिखित प्रश्न पहले नाम लिए गए व्यक्तियों के लिए पूछे जाएंगे । एक व्यक्ति के नाम का चयन करें और फिर उस व्यक्ति के लिए आगे आने वाले प्रश्न पूछें। प्रत्येक व्यक्ति के लिए इस प्रक्रिया को दोहराएं।	
Intensity of Relationship > Intensity of Relationship (1) रिश्ते की तीव्रता > रिश्ते की तीव्रता (1)		(Repeated group)
234	Select name of the person व्यक्ति के नाम को चुनें	1 ... 2 ... 3 ... 4 ... 5 ... 6 ... 7 ... 8 ...
235	In a typical week, on an average how many times do you interact with [intensity_person_name]? एक सामान्य सप्ताह में, औसतन कितनी बार आप [intensity_person_name] से मिलते हैं?	1 Daily प्रतिदिन 2 4-6 times a week सप्ताह में 4-6 बार

Field	Question	Answer
		3 2-4 times a week सप्ताह में 2-4 बार 4 1-2 times a week सप्ताह में 1-2 बार 5 Once a week सप्ताह में एक बार 6 Once a month महीने में एक बार 7 Never कभी नही 8 Only in emergency सिर्फ एमर्जेन्सी/आपातकाल में 666 Not Applicable लागू नहीं 888 Refuse to say उत्तर देने से मना किया
236	In a typical week, on an average how many times do you talk to [intensity_person_name] on phone? एक सामान्य सप्ताह में, औसतन कितनी बार आप फोन पर [intensity_person_name] से बात करते हैं?	
237	In a typical week, on an average how many times do you talk via text message or WhatsApp with [intensity_person_name]? एक सामान्य सप्ताह में, औसतन कितनी बार आप टेक्स्ट मैसेज या व्हाट्सएप के जरिए [intensity_person_name] से बात करते हैं?	
Perceptions about beliefs of known individuals जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा		
instruction3	The following questions needs to be asked for each of the people named previously. Select a person's name and then ask the following questions for that person. Repeat the process for each person. निम्नलिखित प्रश्न पहले नाम लिए गए व्यक्तियों के लिए पूछे जाएंगे । एक व्यक्ति के नाम का चयन करें और फिर उस व्यक्ति के लिए आगे आने वाले प्रश्न पूछें। प्रत्येक व्यक्ति के लिए इस प्रक्रिया को दोहराएं।	
Perceptions about beliefs of known individuals > Perceptions about beliefs of known individuals (1) जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा > जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा (1)		(Repeated group)
238	Select name of the person व्यक्ति के नाम को चुनें	1 ... 2 ...

Field	Question	Answer
		3 ... 4 ... 5 ... 6 ... 7 ... 8 ...

Perceptions about beliefs of known individuals > Perceptions about beliefs of known individuals (1) > Household Decision
जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा > जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा (1) > घरेलू निर्णय

Field	Question	Answer
239	According to [belief_person_name], who should have a greater say on making major household purchases? [belief_person_name] को क्या लगता है बड़े खर्चे जैसे TV या फ्रिज खरीदने का निर्णय किसका होना चाहिए?	1 Wife पत्नी 2 Husband पति 3 Both Equally दोनों का बराबर 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नहीं
240	According to [belief_person_name], who should have a greater say on making daily household purchases? [belief_person_name] को क्या लगता है दैनिक या रोज़मर्रा के घरेलू खर्चे का निर्णय किसका होना चाहिए?	
241	According to [belief_person_name], who should have a great say in decision about health care of children? [belief_person_name] को क्या लगता है कि बच्चों के स्वास्थ्य की देखभाल का निर्णय किसका होना चाहिए?	
242	According to [belief_person_name], who should have greater say in the decision of children's schooling? [belief_person_name] को क्या लगता है कि बच्चों की स्कूल की शिक्षा कहाँ और कैसे होगी - इसका निर्णय किसका होना चाहिए?	
243	According to [belief_person_name], who should have a great say in decision about how wife's earnings should be spent? [belief_person_name] को क्या लगता है कि पत्नी की कमाई कैसे खर्च की जाए - इसका निर्णय किसका होना चाहिए?	
244		

Field	Question	Answer
	According to [belief_person_name], who should have a greater say in decision about how husband's earnings should be spent? [belief_person_name] को क्या लगता है कि पति की कमाई कैसे खर्च की जाए - इसका निर्णय किसका होना चाहिए?	
245	According to [belief_person_name], who should have a greater say about visits to wife's relatives? [belief_person_name] को क्या लगता है कि पत्नी के रिश्तेदारों (मायके) से मिलने जाने का निर्णय किसका होना चाहिए?	
Perceptions about beliefs of known individuals > Perceptions about beliefs of known individuals (1) > Gender Norms जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा > जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा (1) > लिंग मानदंड		
246	Question: How do you think [belief_person_name] would answer the following questions: Yes or No? सवाल: आपको क्या लगता है कि निम्नलिखित के लिए [belief_person_name] का क्या जवाब होगा : हाँ या नही ?	
246A	In [belief_person_name] 's opinion, is it acceptable for an adult woman to travel outside the locality if she wants to? [belief_person_name] की राय में, क्या किसी 18 वर्ष से बड़ी महिला का किसी कारण से इलाके से बाहर जाना उचित है अगर वह चाहती है तो?	1 Yes हा 0 No नही 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नही
246B	In [belief_person_name] 's opinion, should an adult woman work outside of home if she wants to? [belief_person_name] की राय में, क्या एक 18 वर्ष से बड़ी महिला को घर से बाहर काम करना चाहिए, अगर वह चाहती है तो?	
246C	Do you think [belief_person_name] will approve of a married woman earning money if she has a husband capable of supporting her? [belief_person_name] की राय में, क्या एक विवाहित महिला को घर से बाहर काम करना चाहिए यदि उसका पति अच्छा कमाता हो तो?	
246D		

Field	Question	Answer
	In [belief_person_name] 's opinion, if the wife is working outside the home, should the husband help her with household/care duties? [belief_person_name] की राय में, यदि पत्नी घर से बाहर काम कर रही है, तो क्या पति को घर के कामों में उसकी मदद करनी चाहिए?	

Perceptions about beliefs of known individuals > Perceptions about beliefs of known individuals (1) > Beliefs
जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा > जिसे जानते है उस व्यक्ति की मान्यताओं के बारे में धारणा (1) > मान्यताएं

Field	Question	Answer
247	Question: What do you think, will [belief_person_name] agree or disagree with these statements? सवाल: आपको क्या लगता है कि निम्नलिखित के लिए [belief_person_name] का क्या जवाब होगा : सहमत या असहमत ?	
247A	It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family. यह सभी के लिए बेहतर है कि पुरुष घर से बाहर काम करे और महिलाएं घर और परिवार की देखभाल करें।	1 Agree सहमत 2 Disagree असहमत 888 Refuse to say उत्तर देने से मना किया 999 Don't know पता नहीं
247B	It is more important for a wife to help her husband's career than to have one herself. पत्नी के लिए अपना जीविका (करियर) होने से ज़्यादा महत्वपूर्ण है कि वह अपने पति के जीविका (करियर) में मदद करे।	
247C	When a mother works for pay, the children suffer. जब एक माँ घर से बाहर काम करती है , तो बच्चो की देखभाल नहीं हो पाती।	
247D	A working mother can establish just as warm and secure a relationship with her children as a mother who does not work. एक कामकाजी माँ अपने बच्चों के साथ उतने ही स्वस्थ और सुरक्षित रिश्ते को स्थापित कर सकती है जो कि न काम करने वाली माँ कर सकती हैं।	

Own Attitudes खुद की मनोवृति

Own Attitudes > Helping with household chores खुद की मनोवृति > घर के कामों में मदद करना

Field	Question	Answer
248M	On an average how much time do you spend in helping your wife with household chores in a typical week? एक औसत सप्ताह में आप अपनी पत्नी को घर के कामों में मदद करने में कितना समय देते हैं?	1 Do not help मदद नही करते 2 0-30 mins 0-30 मिनट 3 30 mins- 1 hour 30 मिनट - 1 घंटे 4 1-2 hours 1-2 घंटे 5 2-4 hours 2-4 घंटे 6 More than 4 hours 4 से अधिक घंटे 888 Refuse to say उत्तर देने से मना किया
248F	On an average how much time do you spend on completing household chores like cooking, cleaning, shopping etc alone in a typical day? (Record according to an average week by multiplying the response with 7) एक औसत दिन में आप घर के कामों को अकेले पूरा करने में कितना समय लगाते हैं जैसे खाना पकाना, सफाई करना, खरीदारी करना आदि? (जवाब को 7 से गुणा करके औसत सप्ताह के हिसाब से रिकॉर्ड कीजिए)	1 0-7 hours 0 - 7 घंटा 2 7-14 hours 7 - 14 घंटे 3 14-21 hours 14 - 21 घंटे 4 21-28 hours 21- 28 घंटे 5 28-35 hours 28-35 घंटे 6 More than 35 hours 35 से अधिक घंटे 888 Refuse to say उत्तर देने से मना किया
249F		1 Do not help

Field	Question		Answer
	On an average how much time does your husband spend in helping you with household chores in a typical week? एक औसत सप्ताह में आपके पति को घर के कामों में आपकी मदद करने में कितना समय लगता है?		मदद नही करते
		2	0-30 mins 0-30 मिनट
		3	30 mins - 1 hour 30 मिनट - 1 घंटे
		4	1-2 hours 1-2 घंटे
		5	2-4 hours 2-4 घंटे
		6	More than 4 hours 4 से अधिक घंटे
		888	Refuse to say उत्तर देने से मना किया
Own Attitudes > Household Decisions खुद की मनोवृति > घरेलू निर्णय			
250	Who should have a greater say on making major household purchases? आपको क्या लगता है बड़े खर्चे जैसे TV या फ्रिज खरीदने का निर्णय किसका होना चाहिए?		
251	Who should have a greater say on making daily household purchases? आपको क्या लगता है दैनिक या रोज़मर्रा के घरेलू खर्चे का निर्णय किसका होना चाहिए?		
252	Who should have a great say in decision about health care of children? आपको क्या लगता है कि बच्चों के स्वास्थ्य की देखभाल का निर्णय किसका होना चाहिए?		
253	Who should have greater say in the decision of children's schooling? आपको क्या लगता है कि बच्चों की स्कूल की शिक्षा कहाँ और कैसे होगी - इसका निर्णय किसका होना चाहिए?		
254	Who should have a great say in decision about how wife’s earnings should be spent?		

Field	Question	Answer
	आपको क्या लगता है कि पत्नी की कमाई कैसे खर्च की जाए - इसका निर्णय किसका होना चाहिए?	
255	Who should have a greater say in decision about how husband's earnings should be spent? आपको क्या लगता है कि पति की कमाई कैसे खर्च की जाए - इसका निर्णय किसका होना चाहिए?	
256	Who should have a greater say about visits to wife's relatives? आपको क्या लगता है कि पत्नी के रिश्तेदारों (मायके) से मिलने जाने का निर्णय किसका होना चाहिए?	
Own Attitudes > Gender Norms खुद की मनोवृति > लिंग मानदंड		
257	How would you answer the following questions: Yes or No? निम्नलिखित प्रश्नों के लिए आपका क्या जवाब होगा : हाँ या नही ?	
257A	In your opinion, is it acceptable for an adult woman to travel outside the locality if she wants to? आपकी राय में, क्या किसी 18 वर्ष से बड़ी महिला का किसी कारण से इलाके से बाहर जाना उचित है अगर वह चाहती है तो?	1 Yes हाँ 0 No नहीं 888 Refuse to say उत्तर देने से मना किया
257B	In your opinion, should an adult woman work outside of home if she wants to? आपकी राय में, क्या एक 18 वर्ष से बड़ी महिला को घर से बाहर काम करना चाहिए, अगर वह चाहती है तो?	
257C	Do you approve of a married woman earning money if she has a husband capable of supporting her? आपकी राय में, क्या एक विवाहित महिला को घर से बाहर काम करना चाहिए यदि उसका पति अच्छा कमाता हो तो?	
257D	In your opinion, if the wife is working outside the home, should the husband help her with household/care duties? आपकी राय में, यदि पत्नी घर से बाहर काम कर रही है, तो क्या पति को घर के कामों में उसकी मदद करनी चाहिए?	
Own Attitudes > Beliefs खुद की मनोवृति > मान्यताएं		

Field	Question	Answer
258	Would you agree or disagree with the following statements? निम्नलिखित बयानों के लिए आपका क्या जवाब होगा : सहमत या असहमत ?	
258A	It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family. यह सभी के लिए बेहतर है कि पुरुष घर से बाहर काम करे और महिलाएं घर और परिवार की देखभाल करें।	1 Agree सहमत 2 Disagree असहमत 888 Refuse to say उत्तर देने से मना किया
258B	It is more important for a wife to help her husband's career than to have one herself. पत्नी के लिए अपना जीविका (करियर) होने से ज़्यादा महत्वपूर्ण है कि वह अपने पति के जीविका (करियर) में मदद करे।	
258C	When a mother works for pay, the children suffer. जब एक माँ घर से बाहर काम करती है , तो बच्चो की देखभाल नहीं हो पाती।	
258D	A working mother can establish just as warm and secure a relationship with her children as a mother who does not work. एक कामकाजी माँ अपने बच्चों के साथ उतने ही स्वस्थ और सुरक्षित रिश्ते को स्थापित कर सकती है जो कि न काम करने वाली माँ कर सकती हैं।	

WILLINGNESS TO WORK: IMPORTANT FACTORS काम करने के लिए तैयार: महत्वपूर्ण कारक

WILLINGNESS TO WORK: IMPORTANT FACTORS > Important factors
काम करने के लिए तैयार: महत्वपूर्ण कारक > महत्वपूर्ण कारक

Field	Question	Answer
259w	According to you, which of the following are the most important reasons that affect the decision for women to work for pay? आपका घर से बाहर काम करना किन-किन चीज़ों पर निर्भर करता है ?	
259m	According to you, which of the following are the most important reasons that affect the decision for women to work for pay? आपकी पत्नी का घर से बाहर काम करना किन-किन चीज़ों पर निर्भर करता है ?	
259A	Household chores/duties and child care	1 Yes हाँ

Field	Question	Answer
	घर और बच्चों की देखभाल कैसे होगी	0 No नहीं 888 Refuse to say उत्तर देने से मना किया
259B	Family permission and support परिवार की अनुमति और समर्थन	
259C	Husband's salary पति की कमाई से गुज़ारा चलता है या नहीं	
259D	More women at workplace काम की जगह पर महिलाएँ है या नहीं	
259E	More people at workplace of same caste काम की जगह पर अपनी जाति के लोग है या नहीं	
259F	Work at home facility काम घर से हो सकता है या नहीं	
259G	Wage rate/ Salary मजदूरी दर/वेतन; सैलरी कितनी मिलती है	
259H	Any other कोई अन्य	
259I	If other, please specify अन्य हैं, तो कृपया स्पष्ट करें।	
WILLINGNESS TO WORK: IMPORTANT FACTORS > Constraints काम करने के लिए तैयार: महत्वपूर्ण कारक > काम करने में बाधाएँ		
260	What according to you are constraints that women face in your locality in working for pay? Select all the applicable constraints. आपके इलाके में क्या दिक्कतें/बाधाएँ हैं जो घर से बाहर काम करने में महिलाओं को सामना करनी पड़ती हैं? सभी लागू बाधाओं का चयन करें।	1 Non-availability of jobs नौकरियों की कमी 2 Non-availability of safe jobs सुरक्षित नौकरियों की कमी 3 Low wages/salary कम मजदूरी/सैलरी 4 Household chores/duties घर के काम/कर्तव्य 5 Child care बच्चो की देखभाल 6 Family permission and support परिवार की अनुमति और समर्थन

Field	Question	Answer
		777 Other अन्य
261	If other, please specify. Enter 666 otherwise. अन्य हैं, तो कृपया स्पष्ट करें। अन्यथा 666 दर्ज करें।	

WILLINGNESS TO WORK: IMPORTANT FACTORS > Preferred Jobs
काम करने के लिए तैयार: महत्वपूर्ण कारक > पसंदीदा नौकरियां

Field	Question	Answer
262	According to you, what kinds of work would you like your wife to do if she had to work for pay? Select all that apply आपके अनुसार, यदि आपकी पत्नी को काम/जॉब करना हो तो आप क्या काम पसंद करेंगे? लागू होने वाले सभी का चयन करें।	1 Govt job in govt establishment (e.g. office, school, hospital) सरकारी नौकरी (जैसे कि सरकारी स्कूल या अस्पताल या ऑफिस में) 2 Private job in private establishment (e.g. office, school, hospital) प्राइवेट नौकरी (जैसे कि प्राइवेट स्कूल या अस्पताल या ऑफिस में) 3 Factory job फैक्ट्री में काम 4 Construction site बेलदारी या कंस्ट्रक्शन साइट पे काम 5 Domestic help घरों में झाड़ू/पोछा या खाना बनाने का काम 6 Home based work कोई काम जो घर से हो सके 777 Other अन्य
263	If other, please specify. Enter 666 otherwise. अन्य हैं, तो कृपया स्पष्ट करें। अन्यथा 666 दर्ज करें।	
264	According to you, what kinds of work would you like to do if you had to work for pay? Select all that apply.	

Field	Question	Answer
	आपके अनुसार, यदि आपको काम/जॉब करना हो तो आप क्या काम करना पसंद करेंगी? लागू होने वाले सभी का चयन करें।	
265	If other, please specify. Enter 666 otherwise. अन्य हैं, तो कृपया स्पष्ट करें। अन्यथा 666 दर्ज करें।	