Social Networks, Gender Norms and Women's Labor Supply: Experimental Evidence using a Job Search Platform *

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Abstract

Using a cluster randomized control trial, we study the role of women's social networks in improving female labor force participation. In the first treatment arm, a hyper-local digital job search platform service was offered to a randomly selected group of married couples in low-income neighbourhoods of Delhi (non-network treatment). In the second treatment arm, the service was offered to married couples and the wife's social network (network treatment), to disentangle the network effect. Neither couples nor their networks were offered the service in the control group. Approximately one year after the intervention, we find no significant impact in wife's likelihood of working in the network treatment group relative to the control group. Instead, we find a significant improvement in their husbands' labor market outcomes, including likelihood of working, work hours and monthly earnings. In contrast, home-based self-employment increased among wives in the network treatment group. We argue that our findings can be explained by the gendered structure of social networks in our setting, that reinforces (conservative) social norms about women's (outside) work.

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1 Introduction

Peer effects have been shown to increase female labor force participation in many developed countries via social learning (Nicoletti *et al.*, 2018; Maurin & 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 female 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 women's labor market outcomes in low income settings.

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 at no cost, and aimed to lower job search costs. In the first treatment arm, the service was offered to a randomly selected group of married couples (non-network treatment).[1] In the second treatment arm, the service was offered to married couples *and* the wife's peer network (network treatment), in order to disentangle the network effect. Neither couples nor their network were offered the service in the control group.

Approximately 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 4.4 percentage points relative to the control group (equivalent to 4.6% of the baseline mean), while workdays (per week) increased by 55.2% (compared to baseline mean of 5.7 days per week) and the hours worked per day increased by 58.5% (compared to baseline

[1]The service was offered to the married couple together rather than each spouse separately 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).

mean of 8.55 hours per day). As a result, husbands' monthly earnings more than tripled in the network treatment group compared to the control group. We find no significant impact on labor market outcomes of husbands 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 & 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 male relatives who constitute nearly a quarter of a wife's network on average. Such a gendered structure of social networks 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 & Magruder, 2012; Caria *et al.*, 2020). This is confirmed by our finding that only the male peers in the wives' networks experienced a significant improvement in employment outcomes.

In contrast, we find that self-employment among wives in the network treatment group increased by 4.5 percentage points, which is equivalent to a 40.9% increase compared to baseline mean. 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. We document a high preference for home-based work for women (over 80%) and strong support for male bread-winner norm by both husbands and wives in 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 took up home-based work, such as tailoring. Thus, harnessing women's 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 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 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 pandemic 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 search platforms in further boosting demand for women's labor at this time.However, we find that women registered for fewer job profiles, preferred to work at a distance that was half of what men were willing to travel, and expected earnings that were double their current market wages.[2] These preferences and misaligned beliefs may have played a role in lowering the flow of job offers to women than expected, and cannot be completely disentangled from social norms that restrict their work choices, mobility, and access to labor market information I am not sure if this argument is relevant here anymore since we are arguing overall job offer rate wasn't lower for wives than husbands. On the other hand, the positive employment effect for husbands does not appear to be driven by pandemic-induced job losses which occurred immediately after our intervention. We find no differential impact on husbands' employment outcomes in the network treatment group

[2]Mismatch between beliefs and actual job market prospects can further constrain the labor market outcomes of women by distorting their search strategies as shown by Abebe *et al.* (2020) using a job fair intervention in Ethiopia.

either by job loss during the pandemic or employment status right after the pandemic-induced lockdown.

Our paper contributes to the rich literature on the role of peer effects in driving various economic outcomes, including agricultural technology adoption (Beaman *et al.*, 2021; BenYishay & 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.*, 2016), family planning and contraception (Anukriti *et al.*, 2022), and autonomy (Kandpal & 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.[3] 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.[4] 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.

Our paper also ties into the literature on labor market frictions that differentially impede

[3]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 & Wortley, 1990), it may not be advantageous in improving labor market outcomes, for which weak-ties are critical (Calvo-Armengol & Jackson, 2004; Mortensen & Vishwanath, 1994).

[4]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.

women's labor force participation.[5] For example, women's restricted mobility and outside interactions, often rooted in social norms, may lower their awareness and information about economic opportunities compared to men (Field *et al.* (2010) (entrepreneurship); Lindenlaub & Prummer (2021) (white-collar sector)), leading to fewer weak ties ((Calvo-Armengol & Jackson, 2004; Mortensen & Vishwanath, 1994)), higher job search costs and hence lower employment. Digital labor market platforms can offer a potential solution to level the 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 & Sen, 2022; Dhia *et al.*, 2022),[6] 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 outlines the experiment design and the data. The empirical strategy and results, along with robustness checks, are presented in Section 3.4. We discuss mechanisms that can explain our findings in Section 5. Section 6 concludes.

[5]Women exhibit limited physical mobility stemming from social norms (MacDonald, 1999), safety concerns (Dean & Jayachandran (2019); Chakraborty *et al.* (2018); Eswaran *et al.* (2013)) and the disproportionate burden of home production on women (Afridi *et al.*, 2022). As a consequence, relative to men, women may have higher job search costs, and digital labor market platforms can theoretically benefit women more.

[6]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.

2 Sampling, Intervention and Experimental Design

2.1 Sampling

We implemented a cluster-RCT in the National Capital of Delhi, India, between May 2019 and June 2021. 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).[7] However, the employment rate (93.85% for men and 16.73% for women) is lower (by 2.62% and 8.98%, respectively) despite higher years of formal education than the national average for both men and women (PLFS, 2018-19).

Since household listing for electoral purposes is publicly available, we used assembly constituencies (ACs) and the Electoral Board (EB) wards therein (rather than Census wards) for our sampling frame. EBs with a fair amount of slum clusters and slum dwellers (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 EB wards comprising of relatively poorer and less educated residents located close to planned industrial estates with light industries (e.g. footwear, garments where women constitute a significant proportion of workers) that often provide employment opportunities in these areas. The sampled wards were spread across 11 ACs within 5 districts of Delhi - West, North, North-west, Shahadra, and North-east.[8] For each sampled EB the polling station (PS) data was extracted.[9] A random sample of about 10 polling stations for each of the 11 sampled ACs was drawn. 15 households from each polling station were randomly sampled for inclusion in the study. A household was considered eligible for the study if it had at least one married couple in the age group of 18-45 years, individuals

[7]Delhi's age composition is comparable to the national average - 47% of India's population is 18 - 45 years old of which 60% men and 76% women are married. In line with the higher cost of living in urban regions, the average monthly per-capita consumption expenditure in Delhi is 3,500 INR compared to the national average of 2,250 INR (PLFS, 2018-19).

[8]Delhi consists of 11 districts and over 300 EB wards. Wards comprising fully of planned regular colonies which consist of higher-income households were excluded from our sample frame.

[9]See https://ceodelhi.gov.in/Content/List_of_Polling_Station.aspx

who were likely to be engaged in the labor force, and women are more likely to have home production responsibilities, including child care.

Figure 1 shows the geographical spread of the sampled 11 ACs and the 108 polling stations, which form our primary sampling unit. The average distance (straight-line) between any two pairs of polling stations is 10.6 kms.[10]

2.2 Intervention: Job search technology

We partnered with a job-matching platform, HelpersNearMe - a hyperlocal app-based job aggregation platform, that connects potential employers directly with multiple blue-collar workers located physically close to them for permanent or temporary hiring, much like Uber. Once the respondent registers on the aggregator's portal, employers who are looking for a worker whose profile matches that of the respondent, are matched by the platform's algorithm (e.g. on location, type of work - either short-term gigs or long-term contracts, wage offer). The employer can then call the matched worker on her registered phone number with the job offer.

The job-matching platform did not require the respondent (a potential employee) to have a smartphone, a feature phone was sufficient to receive calls from the matched, potential employer. There was no registration cost for the respondent, who only needed to provide an ID (for verification purposes) and at the time of registration provide information on previous work experiences and their job preferences to the platform. This information would then allow the platform to match the individual with potential employers.[11] Since workers can 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 could accept a job offer

[10]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.

[11]Employers who obtain a match pay a service charge to the platform. No payments are required of the worker for a successful match. The minimal worker registration fee, for verification purposes, was paid by the research project.

as per her preferences, including location and salary. Note that the platform could only record accepted job offers and not those that were rejected.

2.3 Experimental Design

Following the baseline survey, the 108 polling stations in our study were randomly assigned to one of the following three arms with 36 clusters each. In the non-network treatment arm (T1) we provided information about an efficient way to search for jobs, i.e. the job search platform, to each individual separately. The research team visited the randomly sampled households and 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 that we developed with a beneficiary of the platform. The testimonial video was tailored to the gender of the respondent. Thereafter, we offered to register the respondent (both woman and her husband, separately) on the job-matching platform. Since labor supply decisions are typically joint and one of our objectives was to assess the role of gender norms, (which are very strong in our context as discussed later), by design the couple was aware of each other's platform registration offer and registration decision.

Once an individual expressed interest in registering we passed on her 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 onboarding). In the network treatment arm (T2) the same procedure was followed as in T1. Thereafter, we offered to register up to two of the wife's peers in her network for this service during the intervention visit. In the control group (C) we did not offer to register the respondents or their network to the job-matching platform.[12]

While the registration offers were made in person to the couples, the offer to register up to two of the wife's peers whom she could select from her social network (reported at

[12]Besides individuals declining to formally register after showing interest, registrations could also fail due to verification issues at the platform's end.

baseline), was made by phone after the visit to the main respondents. If the wife suggested names that were not in the top two rank-ordered baseline network list, these new peers were also surveyed and offered platform registration. Of the individuals offered treatment, 70% husbands and 65% wives showed interest in registering. The final registration rate was lower at 24% in non-network and 26% in the network treatment. Amongst the wives' peers who were offered registration the proportion of interested and registered rates were 72% and 35%, respectively.

3 Data, Summary Statistics and Estimation

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.[13]

[13]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,

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.[14] 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.

To measure the impact of the intervention on the respondents' and the treated networks' work status, we conducted two follow-up surveys. Endline 1 was conducted after approximately 6 months (Aug-Nov 2020) while Endline 2 was conducted over a year (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 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 job-matching platform from the date of registration until June 2021.[15] The timeline of the study is summarized in Table 1.[16]

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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".

[14] 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.

[15] As mentioned previously, because the job matching platform did not require a smartphone to receive job offers, at the platform end data on job offers was incomplete. The platform only recorded whether a match took place or not. Hence we collected detailed self-reported data on job offers, as well, during both endline surveys.

[16] Our study coincided with the pandemic-induced stringent national lockdown in India which began on March 24 and eased by August 2020. Note that our baseline survey of the couples was conducted in person but due to the onset of the pandemic, we switched to phone interviews thereafter. Our first endline conducted between 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, when cases surged from mid-April 2021, we switched to phone interviews from

Our original sample consisted of 3,127 couples (1,543 husbands and 1,584 wives) from 1,613 households across 108 polling stations, as shown in Table 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. 1514 couples.[17] 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. 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 insignificant effects 6 months after intervention (Endline 1), which is attributable to the economic shut-down during the pandemic (see Appendix Table A.1). [18]

3.2 Summary statistics

Table 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

the end of April until the end of the survey round in June 2021.

[17] Of the original sample of 3,127 couples, 99 individuals were unmatched to their spouse. We drop the unmatched individuals and follow the matched couples over time.

[18] 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.

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. Over 1/3rd of the sampled households are natives of Delhi and have lived at the current location for over 28 years.

Panel B records the characteristics of individuals, i.e. the husband-wife couple, in our sample. They are relatively young (32.7 years), with some education (over 60% have above the primary level of education) and high usage (94%) of mobile phones. The employment rate, irrespective of gender, is 60%, comparable to the married individuals in the 18 - 45 age group in Delhi. 16% are engaged in casual labor, 21% are self-employed and 22% have salaried jobs in government and private institutions.[19] The unemployment rate is low at 3%, while 38% of the sample is not looking for work and, therefore, not in the labor force.[20] The average individual earnings was 6,028 (11,000) INR per month unconditional (conditional) on employment status. Panel C of Table 2 summarizes the characteristics of four rank-ordered peers listed at baseline These peers are comparable in age, education, and work status to the main respondents.

In Appendix Table A.2, we show the balance across treatment groups by household characteristics. We do not find any significant difference across treatment arms in the demographics (household size, caste categories, religion, joint family structure, number of young children) or indicators of socio-economic well-being (asset index, ownership of *pucca* house, ration card, and usage of tap water). We find no significant differences in households being natives of Delhi and the years they have been staying in the current location, except for a marginally significant difference in the asset index between T1 and T2.

Appendix Table A.3 shows the balance check for the individual-level characteristics of wives

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

[20] 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.

and their husbands. Wives (husbands) list about 3.9 (3.1) unique names of peers in the social network survey. Other than the pairwise difference in the network size (number of unique peers) between the two treatment arms for wives and the difference in the unemployment rates in T1 (T2) relative to the control group for wives (husbands) (p<0.10), we find no significant differences across all other individual characteristics.[21] Note that the p-value of the F-stat of joint significance of the observable characteristics at both the household and the individual level in each treatment arm is quite high. Overall, our baseline data suggests successful randomization into the three arms at the household as well as the individual level.[22]

3.3 Gender differences

Labor market participation: The gender differences in the overall labor force participation statistics are shown in Panel A of Table 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 were mostly engaged in salaried jobs, of the wives working (24%) a majority are self-employed as shown in Panel A of Table 3. 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, of the sample that registered on the platform. Wives who registered on the job portal expected an average salary of around 10,500 INR (133% higher than the average baseline earnings of women who were working), while husbands expected 13,300 INR or 8% higher than their average baseline earnings. This mismatch in expected

[21]The individual characteristics considered are age (in years), education (above primary school), type of work, years of marriage, number of children, usage of mobile, received skill training, network size, number of friends whose mobile numbers were provided to survey team, whether native of Delhi and the years lived in Delhi, index of gender attitudes and decision-making power of wives.

[22]The average characteristics are also balanced for the original, unmatched sample of households and individuals.

and actual earnings continues to 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.[23]

Social network structure: We observe sharp gender differences in the social network structures reported in Panel B of Table 3. First, wives' social networks are more narrow and home-bound – 75% of wives' peers are non-coresident relatives and 21% are neighbors. Thus, a significantly larger proportion of wives' network vis-a-vis the husbands' (39% relatives and 17% neighbors) consists of family relations and individuals residing in close proximity. 37% of husbands' peers are friends but this category constitutes only 4% of wives' networks. Women report almost none of their co-workers (recall 24% of wives report working) as peers. Hence, there is significant overlap of wives' and husbands' social connections due to the former's home-bound nature. Second, women's social connections are overwhelmingly female (71%), whose employment status is as low (19% - 36%) as their own, as shown in Appendix Table A.4, Panel B relative to men's network structure in Panel A of the same Table.[24] Moreover, (fe)male non-co-residing relatives constitute (57%) 23% of the wife's network (Table A.4 in the Appendix). This structure of women's social network, which is likely to be less amenable to obtaining job information and referrals intensified at intervention, as shown in Table 2, Panel C.[25] 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%).

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[23]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 were 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) that women were.

[24]These data are based on the more detailed information gathered from up two peers per respondent surveyed over phone.

[25]881 individuals (peers) were suggested by wives at intervention in T2, of which 153 had been surveyed at baseline.

Social norms and work preferences: Table 4 indicates a high prevalence of regressive attitudes towards women working by both husbands and wives. Panel A summarizes agreement with gender regressive statements that were asked in privacy of the respondent. At least 80% of both wives and husbands agree that women should primarily be homemakers, although wives are 8 pp less likely to agree that "it is much better if men work while women take care of the home." However, wives are more likely to support their husband's career and prioritize relationship with children over market work (more wives say "woman should support husband's career" and "working mothers have a poor relationship with her children" than husbands, respectively, in Panel A Table 4)

In Panel B, we summarize responses to progressive attitudes towards women working. Wives are 6 pp more likely to say 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. Note that only 2% of wives and 3% of husbands agree that women should not work.[26]

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

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 employment aggregator service, and 0 otherwise. Thus, the baseline specification is:

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

where Y_{iv} are measures of labor market outcomes of individual i in cluster v at endline. It includes work status (working for pay or not), the number of days worked in a week, the number of hours worked in a day, monthly earnings (INR), and occupation category (casual labor, self-employed or salaried).[27] Work status is a dummy variable that takes value 1 if an individual reports engagement in some 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.

T_v is a dummy indicating whether cluster v is 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).[28]

[27]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 response 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).

[28]Refer to Table 2 for details on the construction of the occupation and other variables, including the asset index.

Our second specification distinguishes between the two types of treatments to estimate and compare their impact as follows:

$$Y_{iv} = \alpha + \beta^1 T_v^1 + \beta^2 T_v^2 + \phi Y_{iv}^0 + X_{iv} + \mu_{iv} \quad (2)$$

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. 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 (1)). The network treatment (T2), in addition to easing job search costs and improving employer-employee matching, also harnesses the wife's network.[29] 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.[30] 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

[29] 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.

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

friends for the employment search service to have a relatively higher positive impact on labor market outcomes ($\beta_1 < \beta_2$ in equation 2) in T2.[31]

4 Main results

4.1 Labor market participation

Table 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 (1) while columns (3)-(4) report it by treatment group as per equation (2).

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 husbandsâ likelihood of working by 4.4 percentage points 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).[32]

Next, we examine the treatment effects on the intensive margin in Table 6, measured by the log of days worked in a week (Panel A) and the log of hours worked in a day (Panel B).[33]

[31]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.

[32]We also analyze the heterogeneity in these treatment effects by baseline demographic characteristics in Appendix Table A.5. We find little statistically significant difference in the outcomes of wives or husbands in the network treatment group by poverty status, caste, religion, education, etc. We find that wives whose peers reported relatively progressive attitudes in baseline are more likely to be working relative to the control group (column (7), Appendix Table A.6).

[33]We add a positive value of 0.01 to the reported workdays/hours to account for the zero values before the log transformation. Results are similar if we use an inverse-hyperbolic sine transformation [$log(y) =$

Wives show no significant overall treatment effect on either dimension of intensive margin (columns (1) and (2)). 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).[34]

In contrast, we find positive treatment effects for husbands on both dimensions of intensive margin (columns (1) and (2)), driven by the network treatment group (T2). In particular, husbands in the network treatment group reported working 55.2% more days per week (Panel A, column(4)), as well as working 58.5% more hours per day, relative to control group (Panel B, column (4)).

4.2 Occupational choice and Earnings

We also examine the impact of the intervention on type of work (self-employed, salaried or casual labor in order to test for occupational shifts in Table 7. We find that, while wives experienced no overall treatment impact on their work status as reported in Table 5, their self-employment in the network treatment group increased by 4.5pp (column (3)). This appears to be accompanied by a reduction in their engagement in causal labor by 2.5pp (not statistically significant), indicating a substitution away from precarious work for wives in the network treatment group. However, such a shift is absent for their counterparts in the non-network treatment, and may be a key factor driving the reduction in their work days and work hours, as reported in Table 6. There is no significant impact in terms of salaried jobs for women in either treatment arm. For husbands, they too appear to be substituting out of casual work into salaried and self-employment, although the estimates are less precise.

Next, we examine whether the observed impact on labor force participation and occupational change affected log of monthly (individual) earnings, as reported in Table 8.[35] The overall

$log(y + (y^2 + 1)^{1/2})$) (results available on request)].

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

[35] Similar to work intensity outcomes, we add a positive value of 0.01 to reported earnings to account for zero values before the log transformation. Results are similar if we use an IHS transformation.

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 more than 80% contraction in their earnings relative to control group (column (3)), consistent with their withdrawal from casual labour 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 treatment group whose income more than tripled relative to control group (column (4)). In order to shed more light on the nature of these additional earnings, we also examine in Appendix Table A.7 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 (5)-(8)). We find that the intervention results in husbands shifting to relatively more secure salaried work (column(2)) and away from vulnerable daily wage (column(6)) and piece-rate (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 work (p=0.66), it is significantly higher for the network treatment husbands relative to the non-network treatment husbands for salary work (p=0.09). This provides further confirmation for our earlier findings on occupational shift for husbands, and the role of the 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.

To summarize, we find that husbands' probability of working, 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. 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.[36]. In contrast, we observe a marginal decline in women's work intensity (and hence, earnings) in the non-network

[36]We continue to find similar effects if we condition the sample on those who working at baseline.

treatment group, driven by 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) who find that voluntary unemployment among vocational trainees rose due to higher expectations following registration on an online job portal in India.

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 A.8 show that our regression 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.[37] For this, we test for the differences in mean baseline outcomes across the treatment arms for the non-attriters and the attriters. Table A.9 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 from the test of mean between the treatments and control group for the non-attriters, and 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

[37] 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. These results are available on request.

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 treated 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.

5 Mechanisms

5.1 Role of social networks

What explains the null effect of the network treatment effect on labor force participation of wives, and the positive and significant effect on labor market outcomes of their husbands? We argue that the gendered nature of 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 neighbours compared to 56% for her husband. Second, there exists significant overlap between wivesâ peers and their husbandsâ peers. Moreover, a quarter of an average wife's peers are her male relatives (e.g. brother-in-laws etc.). Hence, it is likely that men (and husbands) benefited more than women from the diffusion of information about job opportunities from the job portal within the network, while wives' labour market participation remained constrained.

We directly test for this network-based explanation for the positive employment effects of husbands using two approaches. First, we examine the effect of 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 9.[38] 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.[39] Male peers' were more likely to work (column (1)), work longer (Panel A, columns (2) - (3)) and enjoy higher income (column (4)).[40]

Secondly, using self-reported survey data, we also find that conditional (unconditional) on interest in registering on the portal, husbands in the network treatment group (T2) were 15 (5.2)pp more likely to receive job offers as shown in columns (2) and (4), Table 10. Surprisingly, 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).[41]

The husbands who got job offers from the portal are more likely to be employed at endline. Hence, the increased employment of husbands in the network treatment group can be directly achieved through greater sharing of information within the network, and indirectly from referrals from male peers of wife. We find that husbands whose wives had a majority of the treated network constituted by 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 the employment opportunities to their husbands or peers. The possibility of this is further substantiated by a higher likelihood of employment

[38] 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.

[39] 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 systematic difference in network selection between baseline and intervention.

[40] 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.

[41] 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 portal 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.

of husbands if the male peers of the wife got a job offer. 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)

Using baseline data on the relationship with peers in the network of an individual, we find that a movement from the 25^{th} to the 50^{th} percentile of the proportion of peers composed of non-coresiding 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 (Table omitted for brevity and available on request). This indicates that the structure of the social network of the wife constrained her 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.

5.2 Role of social norms

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 A.10) - 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 (results available on request). 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. Since the norms held by wives and husbands around women's work were also relaxed by the intervention (refer Table 11), the husbands might now be more accepting of women taking these work opportunities that also align with their baseline preferences. 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 A.11). Also, they showed no increased interest in sharing the domestic chores with the working wives (see column (16) of Appendix Table A.12). 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.[42]

5.3 Alternative explanations

In this section we attempt to rule out other possible explanations of our findings.

First, it may be argued that there exists insufficient demand for women's labor, especially if job recovery was gender unequal 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, Table 10 indicates that the (unconditional) job offer rate for wives was similar (if marginally higher) to that of their

[42] 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.

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. Secondly, looking at the broader time trends of female labour force participation in Delhi and urban India post-pandemic, we find that female employment rates had already begun to recover from Covid losses around the time of our endline in 2021, , indicating the potential of digital job search platforms in further boosting demand for womenâs labor at this time.

Second, are women less likely to take up new digital technology? However, as Table 9 shows, both wives and husbands had higher registration rates, conditional on interest, in the network treatment group relative to the non-treatment group (column (3)). However, there were no significant gender differences in the take-up of the technology in terms of registration on the platform.[43]

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 in employment outcomes for husbands in T2, either by job loss during the pandemic or employment 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.

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? However, we find that the higher participation in self-employment is driven by wives whose husbands were working at baseline but doesn't differ by their employment status or earnings at endline. This rules out the possible income effect from intervention.

Fifth, it is possible that network-mediated self-employment opportunities, e.g. changes in

[43] We do not find any heterogeneity in our results by mobile phone usage.

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 did 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 an index of regressive and progressive gender attitudes in Table 11 towards working women.[44] Treatment reduces the index of regressive attitudes by 0.2 SD for wives and husbands (columns (1) and (2)), compared to the control group. This is not statistically different from T2 for both sexes (columns (3) and (4)). While we do not find a strengthening of the progressive attitudes, 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 progressive attitudes of husbands. Clearly, access to technology has the potential to increase the perceived returns to wives' work by weakening regressive gender norms.[45] But being treated with the network has no differential effect on these attitudes, strengthening our proposed channel of greater flow of job information in the network treatment, that men took advantage of in T2, relative to T1.

[44] See notes to Table 11 for details on the construction of the gender attitude indices.

[45] For the disaggregated impact of treatment on gender attitudes by each component of the indexes see Appendix Tables A.11 and A.12.

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.

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 of women working closer to home or taking up more flexible jobs to balance home production responsibilities. Though our results suggest that reducing job search costs for women through digital technology can increase the social acceptability of women working outside the home, attempts to boost women's employment and earnings may be futile if restrictive social norms continue to dictate their work choices.

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Figure 1: Sampled districts, and polling stations by treatment status

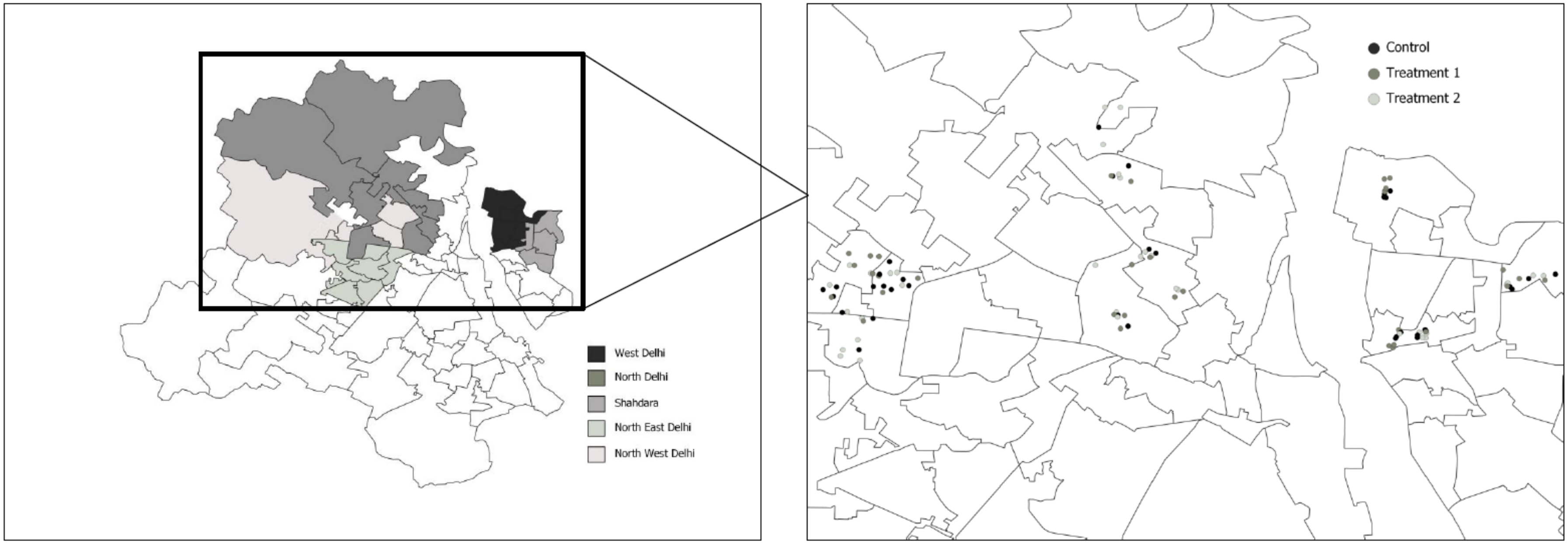

Table 1: Timeline of study

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: 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 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 Networks (by relationship)		
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)	
Neighbour	0.21	0.17	0.04***
	(0.29)	(0.27)	
Co-worker	0.00	0.07	-0.06***
	(0.04)	(0.18)	
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 members in the network. 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 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 work within 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 travel outside locality	0.88	0.88	-0.01
	(0.33)	(0.33)	
Woman work outside home	0.91	0.84	0.06***
	(0.29)	(0.36)	
Woman work even if husband provides	0.6	0.33	0.27***
	(0.49)	(0.47)	
If woman work share 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)	
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, *Domestichelp* is domestic help work, $Home - based$ is home-based work and *Nowork* 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 5: Impact of treatment on work status (1 year after intervention)

	Wife (1)	Husband (2)	Wife (3)	Husband (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 (1) while Columns (3)-(4) report it for equation (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 6: Impact of treatment on work status on the intensive margin (1 year after intervention)

	Wife (1)	Husband (2)	Wife (3)	Husband (4)
	Panel A: Number of days worked in a week			
Treatment	-0.106	0.431**		
	(0.151)	(0.202)		
T1 (without network)			-0.315*	0.317
			(0.160)	(0.213)
T2 (with network)			0.111	0.552**
			(0.176)	(0.212)
ln(Baseline Y)	0.190**	0.080*	0.195**	0.082*
	(0.078)	(0.048)	(0.079)	(0.048)
p-value [T1=T2]			[0.01]	[0.08]
Observations	1,377	1,377	1,377	1,377
R-squared	0.172	0.046	0.177	0.047
Mean Y	1.25	5.69	1.25	5.69
	Panel B: Number of hours worked in a day			
Treatment	-0.123	0.441**		
	(0.152)	(0.220)		
T1 (without network)			-0.330**	0.305
			(0.163)	(0.231)
T2 (with network)			0.090	0.585**
			(0.176)	(0.230)
ln(Baseline Y)	0.208**	0.093*	0.213**	0.094**
	(0.083)	(0.047)	(0.083)	(0.047)
p-value [T1=T2]			[0.01]	[0.05]
Observations	1,377	1,377	1,377	1,377
R-squared	0.175	0.045	0.180	0.048
Mean Y	1.05	8.37	1.05	8.37

Note: The dependent variable in Panel A (B) is a log transformation of the number of days worked in a week (the number of hours worked in a day). Columns (1)-(2) report the combined treatment effect using equation (1) while Columns (3)-(4) report it for equation (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 workdays (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 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 (1) while Columns (3)-(4), (7)-(8) and (11)-(12) report the treatment-wise effect for equation (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 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 (1) while Columns (3)-(4) report it for equation (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 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***	0.947***	0.934***	2.176***
	(0.044)	(0.311)	(0.296)	(0.694)
Observations	394	394	394	394
R-squared	0.160	0.142	0.145	0.130
Mean Y	0.79	6.8	4.43	8843.30
	Panel B: Female peers			
Treatment	-0.025	-0.191	-0.160	-0.284
	(0.030)	(0.183)	(0.181)	(0.372)
Observations	1,428	1,428	1,428	1,428
R-squared	0.139	0.150	0.147	0.146
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 employed, and 0 otherwise. Columns (2)-(4) are the log 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 of the dependent variable for the benchmark group (control + T1) at Endline 1. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 10: 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 and treatment 2 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. 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 11: Impact of treatment on attitudes towards women working (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 Regressive attitudes Index 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 Progressive attitude Index 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 (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 (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

ONLINE APPENDIX

Table A.1: Impact of treatment on labor market outcomes (6 months after intervention)

Variables	Employment 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	0.107	-0.107	0.095	-0.185	0.157	-0.790*
	(0.022)	(0.030)	(0.137)	(0.186)	(0.139)	(0.201)	(0.273)	(0.428)
T2 (with network)	0.015	-0.011	0.136	0.032	0.088	-0.029	0.105	-0.187
	(0.019)	(0.027)	(0.125)	(0.174)	(0.122)	(0.191)	(0.245)	(0.406)
Baseline Y	0.341	0.338*	0.257***	0.154***	0.300***	0.159***	0.279***	0.151***
	(0.359)	(0.180)	(0.049)	(0.055)	(0.055)	(0.053)	(0.053)	(0.055)
p-value [T1=T2]	[.51]	[.51]	[.83]	[.47]	[.96]	[.46]	[.84]	[.14]
Observations	1,401	1,402	1,401	1,402	1,401	1,402	1,401	1,402
R-squared	0.156	0.047	0.167	0.048	0.179	0.047	0.179	0.050
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 reference period and zero otherwise, columns (3)-(4) ((5)-(6)) report the coefficients for the log transformation of the number of days worked in a week (the number of hours worked in a day) and columns (7)-(8) for log transformation of the 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 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 A.2: 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 to on-board the aggregator service, T2 represents treatment in which the main respondents and two of the wife's friends were offered this service and C denotes the control group with no such service being 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 A.3: 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 to on-board the aggregator service, T2 represents treatment in which the main respondents and two of the wife's friends were offered this service and C denotes the control group with no such service being 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 A.4: Structure of social networks by gender of main respondent

	Male Peer				Female Peer			
Relation	Relative (1)	Friend (2)	Neighbour (3)	Work (4)	Relative (5)	Friend (6)	Neighbour (7)	Work (8)
	Panel A: Husband (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)
Employed	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 (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
Employed	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 in 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)
Employed	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: Panel A and B report the characteristics of the top two rank-ordered peers at baseline of the husband and wife, respectively, who were surveyed by phone. In Panel C, the sample is restricted to the two treated peers of the wife in T2, also surveyed by phone. This includes all peers recommended by the wives in T2 for treatment, including those reported at baseline. The 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 A.5: Heterogeneity by demographics in the impact of treatment on work status

(1 year after intervention)

Z	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 # 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 # 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. All individual characteristics are 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 and zero for the base categories ($Z = 0$). The first row reports the regression coefficients for treatment 1 for the base categories while the second row named reports the heterogeneity in the treatment 1 effect by the characteristics. Similarly, the third and the fourth row report the effect for treatment 2 (with network). 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 A.6: The impact of treatment on own work status by own and peers' attitudes towards working women

(1 year after intervention)

Z	Own Attitudes				Peers Attitude			
	Regressive Attitudes		Progressive Attitudes		Regressive Attitudes		Progressive 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 # 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 # 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 Attitudes* indicates relatively restricted gender attitudes (takes a value of one for above median Z-score of regressive attitudes and is zero below median values) and *Progressive Attitudes* indicates relatively liberal gender attitudes (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 row reports the regression coefficients for treatment 1 for the base categories while the second row named reports the heterogeneity in the treatment 1 effect by the characteristics. Similarly, the third and the fourth row report the effect for treatment 2 (with network). 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 A.7: 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 (1) while Columns (3)-(4), (7)-(8) and (11)-(12) report the treatment-wise effect for equation (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 A.8: 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	-0.309*	0.299	-0.323*	0.281	-0.590*	0.617
	(0.027)	(0.021)	(0.161)	(0.215)	(0.163)	(0.233)	(0.322)	(0.468)
T2 (with network)	0.018	0.044**	0.105	0.554**	0.085	0.587**	0.186	1.199**
	(0.029)	(0.020)	(0.176)	(0.212)	(0.177)	(0.230)	(0.349)	(0.467)
Baseline Y	0.921***	0.149	0.197**	0.076	0.216**	0.089*	0.242***	0.086*
	(0.041)	(0.204)	(0.081)	(0.049)	(0.085)	(0.048)	(0.084)	(0.045)
p-value [T1=T2]	[.03]	[0]	[.01]	[.06]	[.01]	[.04]	[.02]	[.06]
Observations	1,364	1,364	1,364	1,364	1,364	1,364	1,364	1,364
R-squared	0.188	0.054	0.184	0.048	0.187	0.048	0.190	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 employed and is zero otherwise. In columns (3)-(8), the dependent variables are log transformed by adding a very small value of 0.01 to account for zero values of dependent variables. Columns (3)-(4) report the log transformed workdays in a week, columns (5)-(6) list log hours of work in a day and columns (7)-(8) report the log 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 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 A.9: 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: Employment 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 Columns (1)-(2) is an indicator variable that takes a value of one if an individual is working and is zero otherwise, columns (3)-(4) report the workdays in a week, columns (5)-(6) list hours of work in a day and columns (7)-(8) report the 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 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. p - values reported in reported in square brackets.

Table A.10: 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 (1) while Columns (3)-(4), (7)-(8) and (11)-(12) report the treatment-wise effect for equation (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 A.11: Impact of treatment on regressive attitudes towards women working (1 year after intervention)

	Attitude 1				Attitude 2				Attitude 3				Attitude 4			
	Wife (1)	Husband (2)	Wife (3)	Husband (4)	Wife (5)	Husband (6)	Wife (7)	Husband (8)	Wife (9)	Husband (10)	Wife (11)	Husband (12)	Wife (13)	Husband (14)	Wife (15)	Husband (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
-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 variable is an indicator variable that takes a value of one if an individual agrees with the regressive attitude and is zero otherwise (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 (1) while Columns (3)-(4) report it for equation (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 A.12: Impact of treatment on progressive attitudes towards women working (1 year after intervention)

	Attitude 1				Attitude 2				Attitude 3				Attitude 4			
	Wife (1)	Husband (2)	Wife (3)	Husband (4)	Wife (5)	Husband (6)	Wife (7)	Husband (8)	Wife (9)	Husband (10)	Wife (11)	Husband (12)	Wife (13)	Husband (14)	Wife (15)	Husband (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
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 variable is an indicator variable that takes a value of one if an individual agrees with the Attitude and is zero otherwise (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 (1) while Columns (3)-(4) report it for equation (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).