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Social Networks, Gender Norms and Labor Supply: Experimental Evidence Using a Job Search Platform*

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Abstract

This paper studies the role of job search frictions and peer effects in shaping female employment outcomes in developing countries. Motivated by a collective model of household decision-making, we conduct a randomized field experiment in Delhi, India where we randomly offer a hyper-local digital job search and matching service to married couples on their own (non-network treatment), together with the wife's peer network (network treatment), or not at all. Approximately one year later, we find no significant impact on wives' overall likelihood of working in either treatment group, but wives in the non-network treatment group reduce their work intensity and casual work, while those in the network treatment group increase their home-based self-employment. Strikingly, husbands' labor market outcomes also improved significantly in the network treatment group. We show theoretically and empirically that our findings can be explained by the home-bound structure of women's social networks that reinforce (conservative) social norms about women's outside-of-home work.

JEL classification: J16, J21, J24, O33
Keywords: social networks, social norms, gender, job-matching platforms, employment

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1 Introduction

Despite growing evidence on the importance of female labor force participation in economic development (Hsieh *et al.*, 2019; Cuberes & Teignier, 2016; Esteve-Volart, 2009), women's employment outcomes continue to lag behind men, both in developed and developing countries (Klasen, 2019). Beyond the common economic explanations, such as education (Altonji & Blank, 1999), technology (Goldin & Katz, 2002; Greenwood *et al.*, 2005), occupational segregation and discrimination (Blau & Kahn, 2017), childcare (Bjorvatn *et al.*, 2022; Nandi *et al.*, 2020) etc., recent research has identified another factor: the job search process itself may disadvantage women. In particular, women may face higher search costs in accessing job information and opportunities (Fletcher *et al.*, 2018). This may be especially severe in developing countries where the majority of jobs are obtained through informal channels, e.g. network referrals, that women are typically excluded from (Beaman *et al.*, 2018). In addition, an emerging literature has also highlighted the role of cultural barriers in the form of social norms that restrict women's mobility and connections outside the home, particularly in developing countries, that may reinforce these economic barriers and further lower women's participation in paid work (Jayachandran, 2021; Bursztyn *et al.*, 2020; Petrongolo, 2019). Yet, there is little research on whether, and how, such economic and cultural determinants of female employment may interact, and whether they can be tackled together.

In this paper, we aim to fill this gap, both theoretically and empirically. We first develop a simple collective model of household decision-making (Chiappori, 1988, 1992) that incorporates frictions arising due to both gender-differentiated job search costs as well as norms against women's outside-of-home work, to explain low female employment in a conservative society. On the one hand, job arrival rate is lower for wives relative to husbands. On the other hand, gender norms lead to a steeper labor supply curve (and hence higher reservation wages) for wives compared to husbands. The model predicts that lowering search frictions and improving the set of available jobs can potentially help to increase employment of wives and dilute gender norms against their working outside of home. However, these effects may also be moderated by the structure of their social network, to the extent that the network helps to either challenge or reinforce regressive gender norms.

We then present evidence from a field experiment that evaluates an intervention designed to reduce these labor market frictions, in the form of access to a digital job search and matching platform in Delhi, India. The platform provides hyperlocal employer-employee matching and job aggregator services to blue-collar workers. In the first treatment arm, the platform service was offered free of charge to a randomly selected group of married couples (non-network treatment) to lower job search costs. The decision to offer the service to both husband and wife was motivated by the extensive evidence documenting that better employment opportunities for women (alone) may invite male backlash and increased risk of domestic violence in conservative settings (Eswaran & Malhotra, 2011; Heath, 2014; Paul, 2016; Guarnieri & Rainer, 2021; Tur-Prats, 2021). In the second treatment arm, the service was offered to married couples and the wife's peer network (network treatment), also free of charge, to directly shift norms by leveraging peer effects in female employment (see e.g. Boelmann *et al.* (2021)). Neither couples nor their network were offered the service in the control group. Interest in the service was quite high in our sample: nearly 65% of wives and 70% of husbands who were offered the service reported being interested. Conditional on interest, nearly 35% of wives and 38% of husbands registered for the service.

We report three key empirical findings. First, approximately one year after the intervention, we find no statistically significant effect on wives' likelihood of working in either treatment group compared to the control group. However, it is worth noting that the point estimate is positive and significantly higher in the network treatment group than in the non-network treatment group. In addition, we observe a significant decrease in the intensity of work and earnings for wives in the non-network treatment group, but no such negative impact is observed for their counterparts in the network treatment group. Specifically, wives in the non-network treatment group reduce their work days (per month) by 1.2 (equivalent to 24% of baseline mean) and their daily working hours by 35% compared to the control group.

Second, in contrast to wives, we find a significant improvement in the labor market outcomes of husbands in the network treatment group, both at the extensive and intensive margins, but not of those in the non-network treatment group. In particular, husbands in the network treatment group experienced a significant increase in their likelihood of working by 4.4 percentage points (equivalent to 4.6% of baseline mean). This is a striking result, given the high baseline level of male employment (96%), and the fact that the network treatment targeted the wife's peers, not the husband's. Furthermore, their workdays (per month) and daily working hours increased by 8.4% and 8.1% respectively, compared to the control group. Consequently, the monthly earnings of husbands in the network treatment group more than doubled relative to their control group counterparts. Husbands in the non-network treatment group appear to be working as intensively as their counterparts in the network treatment group but without any significant impact on their extensive margin of work or earnings.

Third, the positive but statistically insignificant impact on wives' employment in the network treatment group masks a compositional shift: these wives are 4.5 percentage points (37.5% of baseline mean) more likely to be self-employed in the endline compared to their counterparts in the control group that is mirrored by a reduction, though imprecisely estimated, in their engagement in casual labor. This suggests a shift away from precarious work for wives in the network treatment group. In contrast, while wives in the non-network treatment group also exhibit a similar move away from casual labor, there is no accompanying shift towards self-employment. This is consistent with the reduced intensity of work by these wives discussed above. Furthermore, husbands also display a tendency to transition from casual labor to better, salaried jobs and self-employment, although these shifts are not precisely estimated.

Using our theoretical model, we interpret our findings as follows. First, although access to the job aggregator platform may have helped smooth out some of the job search constraints faced by wives in the non-network treatment group, it may not have been sufficient (in terms of a high enough compensating differential) to overcome the burden of domestic work and the norm constraint (leading to higher reservation wages as per our model) faced by them. Furthermore, as job opportunities simultaneously improved for husbands due to access to the platform, they were more likely to take up these better jobs and/or work longer, owing to their lower reservation prices relative to wives. In turn, this may have further dampened the potential positive effects of the job aggregator platform on wives' employment in the non-network treatment group due to home production responsibilities, leading to these wives to work less intensively during our observation period, and even withdraw from the labor market, especially if they were previously employed in casual, precarious jobs. In contrast, communication with, and learning from, other treated (female) peers in their network may have enabled wives in the network treatment group to counter this negative impact by shifting to self-employment. This is consisted with our finding that at endline, wives in the network treatment group whose treated female peers took up self-employment contemporaneously, are more likely to be self-employed themselves.

Second, our theoretical framework draws attention to the challenges of leveraging peer effects to boost female employment in conservative settings, by highlighting the role of the *structure* of women's network. In line with existing evidence, our model posits that home-based, conservative network structures may reinforce patriarchal norms to keep wives' outside work low (Jayaraman & Khan, 2023), while friend-based, liberal network structures may lower the costs of challenging existing norms (Field *et al.*, 2016; Anukriti *et al.*, 2022). Our muted employment treatment effect for wives in the network treatment group appears to be consistent with the former mechanism: we find that in this group, wives whose baseline social networks included fewer family members were more likely to be working at endline relative to the control group, but this effect is completely reversed for those (majority of) wives whose networks included relatives. Additionally, we also find that wives in the network treatment group who had more conservative peers at baseline (typically relatives) are less likely to be working at endline.[1]

Third, our model also highlights that the same social networks that restrict wives' employment in a conservative setting have the potential to benefit their husbands, owing to the *overlapping* nature of the spouses' respective networks through family members and neighbors. Indeed, our results confirm that in the network treatment group, husbands whose baseline social network overlapped with that of their wives were significantly more likely to be employed at endline. Hence, alongside reinforcing the existing norm of low employment among the wives as discussed above, such home-bound networks may also benefit their husbands by passing on relevant job information, leading to increased job offers and better employment outcomes for those husbands.

In summary, our findings indicate that despite the theoretical promise, reducing search frictions may not necessarily improve women's labor market outcomes due to existing gender norms and the negative externality imposed by their husband's work, within the household optimization process. In addition, a key innovation of our paper is to demonstrate that harnessing women's peer networks to improve their labor market participation may backfire in settings where the nature of their networks reinforce, rather than challenge, gender norms about women's outside of home work. This is consistent with our result that while treatment (both with and without network) attenuated regressive attitudes towards gender roles, it failed to amplify progressive attitudes about women's work, thereby pointing to the stickiness of such norms and the inherent challenges faced in changing them. We rule out several alternative explanations for our findings, including gender differences in access to or use of new digital technology, low demand for women's labor, differential recovery from pandemic-induced job losses by gender, income effects, social comparison effects etc.

Our paper makes two main contributions. First, our paper relates to the literature on labor market frictions that differentially impede women's labor force participation. Restrictions on women's mobility and outside interactions in developing countries[2] may lower their information about economic opportunities compared to men (Field *et al.*, 2010; Lindenlaub & Prummer, 2021), leading to fewer weak ties (Calvo-Armengol & Jackson, 2004; Mortensen & Vishwanath, 1994), higher job search costs and hence lower employment. The increasing popularity of digital platforms that match workers with potential employers online has raised hopes for reducing such costs for women (OECD, 2018; UNWOMEN, 2020), yet there is little scientific evidence on their effectiveness in closing the gender employment gap. Our paper

[1] Family members hold the most conservative attitudes towards women working outside the home in our sample, followed by neighbors. On the other hand, friends of wives have relatively liberal attitudes.

[2] Existing literature has identified several factors limiting women's physical and social mobility, including those rooted in social norms (MacDonald, 1999), safety concerns (Dean & Jayachandran, 2019; Chakraborty *et al.*, 2018; Eswaran *et al.*, 2013), disproportionate burden of home production (Afridi *et al.*, 2022), etc.

fills this gap, going beyond emerging research on digital platforms (Kelley *et al.*, 2022; Jones & Sen, 2022; Dhia *et al.*, 2022; Wheeler *et al.*, 2022) to highlight that the impact of such new job search technologies may not be gender-neutral, particularly in settings when female labor supply decisions are taken jointly by spouses.

Second, we contribute to the rich literature on the role of peer effects in driving economic outcomes, particularly for women.[3] While peer effects have been shown to increase women's employment in developed countries via social learning (Nicoletti *et al.*, 2018; Maurin & Moschion, 2009; Mota *et al.*, 2016) and conformism (Cavapozzi *et al.*, 2021), there is little empirical evidence on whether this extends to low-income settings, and specifically in work outside home to increase women's agency (Anderson & Eswaran, 2009). Our paper advances this literature by highlighting how the structure of women's networks itself may mediate peer effects in labor markets differently in developing countries compared to advanced societies, especially through the distinction between home-bound, family-based peer networks and friends-based networks.[4] This distinction may be particularly relevant for low-income urban women, many of whom migrate to cities post-marriage, and face greater mobility restrictions.[5] Hence, our paper also extends our understanding of women's peer effects in urban, blue-collar contexts, beyond the primarily rural, agricultural settings explored in existing studies.

The paper is organized as follows. Section 2 presents a conceptual framework to motivate our experiment. Section 3 outlines the intervention, experimental design, and sample. Section 4 discusses the data, summary statistics and estimation methodology. The main results are presented in Section 5, while we discuss mechanisms to explain our findings in Section 6. Section 7 concludes.

2 Conceptual Framework

In this section, we outline a simple collective model of household decision-making (Chiappori, 1988, 1992) to explain low female employment in socially conservative settings, and motivate

[3]Existing studies have shown positive peer effects in agricultural technology adoption (Beaman *et al.*, 2021; BenYishay & Mobarak, 2019), microfinance (Banerjee *et al.*, 2013), migration (Munshi, 2020) etc. and specifically for women, in entrepreneurial activity (Field *et al.*, 2016), family planning and contraception (Anukriti *et al.*, 2022), and autonomy (Kandpal & Baylis, 2019).

[4]While home-based network structures can provide 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).

[5]Out-migration data from India's nationally-representative National Sample Survey (NSS) show 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.

our experimental design.

Consider a household (HH) with a husband (m) and wife (f) at time t (baseline). Below we suppress the time dimension to avoid excess notation, but will return to it when discussing HH choices. The collective utility of the HH is given by:

$$U_{HH} = v(w_f.e_f + w_m.e_m) - c(e_f) - c(e_m) + u(H) - I_{Dev} \times [\phi_i(n_i)(e_f - \bar{e}_f^k)^2]$$

where $e_i \in [0,1]$, denotes the fraction of total time (out of a working day) spent working outside of home (OOH), by husbands ($i = m$) and wives ($i = f$). H is the home good, such that $1 - e_m - e_f = H$, and w_i is wages for f(emales) and m(ales). We are interested in how the HH makes the joint decision of the wife's working hours outside of home (OOH), e_f. We assume that both husbands and wives are interested in maximizing joint HH income, subject to norm constraints (such as male breadwinner norm, supported by our evidence in Section 4.3) that apply to the wife's working hours OOH. Note that the costs of non-conformism apply only when the norm is challenged, i.e., $I_{Dev} = 1$ if $e_f > \bar{e}_f^k$ and are zero for employment below the norm (i.e., $I_{Dev} = 0$ if $e_f < \bar{e}_f^k$).

We begin by describing the labor market for wives. On the demand side, jobs are characterized by the wages per unit of work and various features such as flexibility in working hours, commuting time and costs, safety at work, and sharing in production of H. These features are especially important for wives as they may or may not satisfy some of the norm constraints that wives face. We capture these constraints by thinking of a job as a pair (w, e_f): the wages per hour and the minimum OOH hours required in the job. Jobs arrive at a rate r_i, $i = f, m$ per period. Denote the set of cumulative jobs that are available to wives (by endline) as J_f and to husbands as J_m.[6] Figure 1a illustrates one possible set of available jobs for wives, J_f (a frequency distribution).[7]

The **first friction** in the model is the high costs of job search which affects women more than men. One possible reason could be that job search requires physical mobility and women have greater safety issues in traveling in a difficult urban landscape (Borker, 2021; Dean & Jayachandran, 2019; Chakraborty *et al.*, 2018). While men's job search costs are mitigated by job information arriving via their networks, this may not hold for women, as evidenced in Beaman *et al.* (2018). One reason for this might be that men's networks are typically characterised by more "weak ties" (friends rather than family) that provide non-redundant

[6] The job arrival rate is assumed to depend on the duration of time spent on job search and the number of distinct sources (e.g. peers) from where information about jobs is available. Longer search duration and more sources translate into a higher job arrival rate r_i, therefore larger J_f.

[7] Of course J_f need not look like this - it is plausible that the frequency distribution of jobs for women provides high wages only for high OOH work and wages peak at some level.

information on jobs (Granovetter, 1973). Thus, $J_f < J_m$.[8]

Turning our attention to the supply side, and the household optimization problem, deviation from the norm on women's OOH work, $\bar{e}_f$, implies that the HH incurs a costly sanction of $\phi_i(n_i)(e_f - \bar{e}^k_f)^2$, where the norm itself depends on how many women are employed, according to the step function: $\bar{e}^k_f = \underline{e}_f$ (low working hours norm) when $e_f \leq K$ and otherwise $\bar{e}^k_f = \tilde{e}_f > \underline{e}_f$ (high working hours norm). This constitutes the **second friction** in the labor market for women, i.e. the prevalence of gender norms against women working OOH even when it may be feasible and desirable.

Beliefs on the norm are formed by various factors such as communication between HH networks, and depend on the OOH employment of female peers in the network, since these are the people with whom individuals are closely bound. The weight on norms ϕ_i, which affects the extent to which HHs are willing to break norms, depends on the network type n_i of the HH. Peers of the HH could be family relatives, neighbors, friends, work colleagues. Thus, $n_i \in \{C, L\}$, where C is a home-bound or family-based (conservative) network structure and L is a friends-based (liberal) network structure. We think of the network of the HH as the intersection of the husband's and wife's networks: if the wife works OOH she is likely to have friends and work colleagues in her network (hence less overlap with her husband's network) but if she is unemployed, her network is more likely to be comprised of family members (and neighbors) and therefore overlap considerably with her husband's. Friends-based network structures help to challenge norms (Field *et al.*, 2016; Anukriti *et al.*, 2022) while home-bound, conservative network structures reinforce norms (Anukriti *et al.*, 2020; Jayaraman & Khan, 2023).[9]

This additional gender norm constraint makes the labor supply curve for wives steeper than that for husbands, as illustrated by Figure 1b. As the weight on norms $\phi_i(n_i)$ increases, the supply curve of wives becomes steeper, implying that a marginal increase in wages will have a smaller impact on hours supplied for wives relative to husbands.

From the labor supply curve, we can deduce the set of acceptable jobs: these are jobs such that for a fixed e_f the wages offered must be at least as high as the supply curve, depicted in Figure 1b by the area above the supply curves for wives (shaded red) and husbands (shaded blue) respectively.

A significant proportion of women in our sample are self-employed. We model self-

[8] Moreover, there is a well-documented gender wage gap which means that even the jobs that arrive are less well paid for wives, i.e. J_f likely to be well below J_m for each e_i. For example, the Periodic Labor Force Survey of India (2019-20) documents that the average pre-pandemic gender wage gap is 33%.

[9] Example of ways in which peers can affect norms are via information provided by employed women on how to combine work and home production, the monetary and non-monetary opportunity costs of not working OOH (Boelmann *et al.*, 2021).

employment as the outside option for wives: earnings are among the lowest in this category but it satisfies the norms constraint. Any new jobs would be compared to this option and taken up if the wage differential can compensate sufficiently for the lower suitability relative to self-employment. However, setting up a small business (the main form of self employment in our context) is costly and will only be taken up in the absence of alternative job opportunities.[10]

We can now describe how the matching process works. A match occurs if the set of acceptable jobs and the set of available jobs intersect, as shown by the shaded green area in Figure 1c. Note that the likelihood of a successful match is lower when the weight on norms $\phi_i(n_i)$ is high: as Figure 1c illustrates, the labor supply curve for wives may be so steep that there is no intersection between the set of available jobs and the set of acceptable jobs for wives.

This leads to the following observations: First, due to the steeper labor supply curve for wives, even if we assumed that the same set of jobs is available for both husbands and wives, $J_f = J_m$, the husbands would be more likely to accept a job offer first leading to the shifting of the household production constraint for wives (i.e., the leftward shift of the $1 - H - e^*_m$ line in Figure 1c. If wives were initially employed they may end up working less OOH because they need to substitute for the increase in e_m. With a lower job arrival rate for wives relative to husbands (i.e., $r_f < r_m$) or a smaller set of available jobs (i.e., $J_f < J_m$), this negative externality may intensify.

These two frictions reinforce each other, as greater availability of well-paid jobs may change the desire to conform as more women take up employment, thus increasing $\bar{e}^k_f$, leading to norms becoming more liberal as well (see Bicchieri *et al.* (2018) for how norms evolve). Conversely, fewer desirable jobs induce fewer women to take up employment, thereby reinforcing a low norm. Such self-reinforcing nature of norms and job search (social) networks of women may thus give rise to multiple equilibria in women's employment and norms: one with conservative gender norms against women's OOH work sustained by low employment of wives and the other with liberal gender norms and high employment of wives.

Figure 1d graphically illustrates such a multiple equilibria scenario. In particular, we show how the norm changes with e_f: when e_f crosses the threshold K there is a discontinuous jump to a higher norm. In other words, when sufficiently many wives break the norm, the norm itself shifts to the higher one. On the other hand, e_f changes with wages w_f, costs from sanctions ϕ_i, and husband's hours of work, e_m for the same norm – e.g. when wages are

[10]Notably, in our sample only 2% of wives and 3% of husbands agree that women should not work. The remaining 98% of wives and 97% of husbands want women to work and have a desire for work that either aligns with the social norm of *home-based* jobs, or is high status, high paying *salaried* government or private sector job that can offset the cost of deviating from the norm.

higher, e_f is higher even for the same norm, demonstrating the trade-off between higher wages and breaking the norm. HHs with higher ϕ_i or more conservative (home-based) networks are less likely to respond to job opportunities, compared to HHs that place a lower weight on norms or have more liberal networks (due to steeper labour supply curves for wives). Finally, increases in e_m can potentially crowd-out e_f.

Therefore, the key question is: starting from a low norm of $\underline{e}_f$, how can we shift the equilibrium to the high employment, high norm one, $\tilde{e}_k$? Two potential channels present themselves: (A) increasing J_f, and (B) reducing ϕ_i. Channel (A) entails improving the opportunities for suitable jobs to be available for wives. Spending more time on job search and having more peers that can share job information may increase job arrival rate for wives, leading to an upward shift of the J_f curve and expanding the intersection between the set of acceptable jobs and J_f. This can, in turn, catalyze an increase in the take-up of OOH work by wives.

Channel (B) would entail *directly* challenging the low norm of wives' OOH work by simultaneously improving job opportunities for their peers (i.e. leveraging peer effects) that can eventually reduce the cost of non-conformism, $\phi_i(n_i)$.[11] As more women in the network participate in the labor market, the norm ($\bar{e}_f^k$) starts to shift and can gradually modify the beliefs held by the network from conservative to relatively liberal attitudes towards women's OOH work (i.e., a lower $\phi_i(n_i)$). This would lead to a flatter labor supply curve for wives, and increased take-up of OOH work by wives. Moreover, communication with peers may also lead to a faster estimation of the "true" set J_f, since the flow of information about jobs will be larger from private job search as well as information from peers about potential jobs.[12]

However, whether or not this is possible will depend on the structure of the peer network n_i. If the network structure is conservative – i.e. peers are more conservative ($\phi_j > \phi_i$), beliefs on the norm $\bar{e}_f^k$ are lower and the estimation of J_f will be lower – a deviation from the norm is more costly so that gender norms may be reinforced. Thus, job information from the network may be passed on to *husbands* rather than wives or even when women do get more attractive job offers involving OOH work, they may not take them. Note that it is possible that households have higher income when husbands work rather than wives, due to the widely documented gender wage gap (Periodic Labor Force Surveys (PLFS), 2019-20). On the other hand, wives working outside the home may benefit the household in many other ways (see discussion in Fletcher *et al.* (2018)). Welfare effects may therefore be ambiguous.

[11] For instance, by applying for jobs where they can commute together to mitigate safety concerns or using examples of similar women who take up jobs to challenge their own family members.

[12] In fact, our data confirm that the type of jobs wives and their peers look for are essentially the same.

3 Intervention, Context and Design

3.1 Intervention: Job search platform

Our field experiment utilizes a hyperlocal digital job aggregator platform, HelpersNearMe (HNM), to address the two labor market frictions discussed in the conceptual framework above. This nation-wide job-matching platform connects potential employers directly with nearby blue-collar workers for permanent or temporary hiring, much like Uber for taxi services. Since workers may connect with many potential nearby employers without physically looking for work or through any intermediaries or job contractors, this aggregation platform potentially reduces job search costs significantly (for both ends of the market). Workers register on the platform, where they provide information on previous work experiences and their job preferences (including preferred distance to work and expected wages). This information (the set of acceptable jobs) then allows the platform to match registered workers with potential employers who are looking for candidates for specific job profiles based on their search preferences (e.g. location, type of work, tenure i.e. short-term gigs or long-term contracts, expected wages) – equivalent to increasing the set of available jobs for workers. The employer can then call the matched worker on their registered phone number with the job offer. Thus, registered workers are mostly passive on the platform - they cannot reach out to potential employers via the platform, but wait to receive job offers from employers over phone. Any conversation between potential employer and employee is off the platform, but workers can potentially call back an employer who has made an offer, refer or share employer/job details with peers. Workers accept a job offer as per their preferences, including location and wage. This design feature of the platform minimises the chances of workers not

Employers pay an upfront service charge to the platform. No payments are required of the worker for a successful match. There is a minimal expense of 100 INR per person (equivalent to 20-30% of average daily earnings in our sample) for platform registration to meet the cost of verification of worker identity. For our treated participants, this registration fee was paid for by the research project. Note that the platform is unique in catering to the potential constraints of blue-collar workers, particularly women. First, the platform does not require smartphone ownership by these low-income individuals (unlike most other job-matching portals). A feature phone is sufficient to receive calls from matched potential employers. This lowers barriers to entry into blue-collar jobs, especially for women who are less likely to own smartphones in our context. Second, the platform matches workers to employers hyperlocally. Hence workers can find jobs closer to home, which we show later is preferred by women in our sample. Given these features, it is not surprising that as of 2019-20, women made up 60% of all workers registered on the platform. We provide more details to substantiate the balanced gender composition of registered individuals and the types of work offered on the platform in Appendix Table A.1.

3.2 Context and Sample

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

Our sampling strategy is described in Appendix Section A. Our random sample of just over 1,600 households was drawn from 5 districts of Delhi and 11 sampled Assembly Constituencies (AC) therein. Within each AC, a stratified random sample of about 10 polling stations (PS) was drawn, and within each sampled PS, 15 households were randomly sampled for inclusion in our 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.

Figure A.1 shows the geographical spread across Delhi of the sampled 108 polling stations, which form our primary sampling unit (cluster). The average distance (straight-line) between any pair of polling stations is 10.6 kms. To minimise the risk of contamination, the polling station was chosen as the unit of randomization in our cluster RCT design.

3.3 Experimental Design

Our experimental design involves two treatment arms. First, in the non-network treatment arm (T1), the job aggregator platform is introduced to couples. Conditional on registration, the platform is expected to reduce the costs of job search for both wives and husbands, but differentially benefit wives more as they face higher search costs to begin with, leading to larger percentage increase in volume of jobs J_f relative to J_m via Channel (A) as discussed in our conceptual framework in Section 2.

Second, in the network treatment arm (T2), we introduce the job aggregator platform to the couple *and* the peer network of the wife. Besides lowering search costs for a larger number of women via Channel (A), this is also equivalent to expanding the reach of the platform by a doubling of T1 (2 peers in addition to the couple), that can potentially lead the treated HHs to update faster their estimate of the job opportunities available for wives J_f via information on opportunities that their peers have received. In addition, T2 directly also targets norms, using peer effects via channel (B) as discussed in Section 2. Depending on the structure of the peer network (friends-based, liberal or home-based, conservative), providing access to the job platform to peers as well as the couple may (or may not) lead to a higher probability of women taking up OOH work by, e.g., reducing the cost of initiating discussions with husbands, captured by a reduction in ϕ_i.

The sampled 108 polling stations were, thus, randomly assigned to one of three arms, with 36 clusters each: the non-network treatment arm (T1), the network treatment arm (T2), and the control (C). In the non-network treatment arm, we visited the sampled households to provide information about the job search platform to the woman and her husband, separately. We provided detailed information on how the job matching platform works, the registration process, and its potential benefits in obtaining work for each respondent. This was followed by showing a testimonial video, tailored to the gender of the respondent, that we developed with beneficiaries of the platform. Thereafter, we offered to register the respondent (both the woman and her husband) on the job-matching platform at no cost. By design, the couple was aware of each other's platform registration offer and registration decision.

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

While the registration offers to all the couples were made in person, the peers selected by the wife in the network treatment group were offered the platform registration over phone. If the wife suggested peers who were not in their baseline network list (described in detail in Section 4.1 below), these new peers were then also surveyed at this time, and offered platform registration. Once an individual expressed interest in registering (in either treatment group) we passed on their ID and mobile phone number to the job-matching platform, which would then follow up with a phone call to verify details and formally register the job preferences of the individual within 24 hours (the process of 'on-boarding').

Of the individuals offered treatment, husbands and wives showed comparable interest in registering (70% of husbands and 65% of wives). The proportion of wives who showed interest was similar in both treatments (about 64%), while husbands in T1 showed slightly greater interest (73% vs. 66%). Conditional on interest, 37% successfully registered on the portal - higher in the network treatment arm (40%) than the non-network treatment arm (34%), and for both husbands and wives. Amongst the wives' peers who were offered registration, the proportion interested and registered (conditional on interest) was 70% and 47%, respectively.[13] See Appendix Table A.2 for further details.

[13]Besides individuals declining to formally register after showing interest, registrations could fail due to

4 Data, Summary Statistics and Estimation

4.1 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 toward 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.[14]

Thereafter, 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.[15] 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

verification issues at the platform's end. Note that while it is possible that respondents in T1 could, on their own, inform their peers about the platform, our data confirms very few actually do. Only 4% of non-treated peers report being informed about the platform by their friends/relatives, and of those, only 0.07% registered on the platform (data from both our survey and the platform). Of the treated peers, 98% reported being informed about the portal by our research team.

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

[15]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.

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 peers' work status and related outcomes, we conducted two follow-up surveys. Endline 1 was conducted approximately 6 months after the intervention (Aug-Nov 2020) while Endline 2 was conducted about 14 months after the intervention (Apr-June 2021). At both endlines, we resurveyed the main respondents and their peers (including any new peers at intervention). We also obtained administrative data from the job-matching platform on the sample of registered respondents' (main respondents and peers) reported job preferences and other details recorded at the time of registration, as well as job offers and acceptances from the date of registration until June 2021. However, platform data on job offers only recorded whether a match took place or not, i.e. accepted offers. Hence we also collected detailed self-reported data on job offers (accepted or not) during both endline surveys. The timeline of the study is summarized in Table A.3.[16]

Our original sample consisted of 3,127 individuals (1,543 husbands and 1,584 wives) from 1,613 households across 108 polling stations, as shown in Table A.3. 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.[17] Throughout our analysis, we restrict the data to matched husband-wife pairs interviewed at baseline, i.e. 1,514 couples.[18] With the matching restriction, attrition remains below 5%: 98.28% of the couples from baseline were followed-up at Endline 1 and 95.48% at Endline 2.

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

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

[17]In Appendix Section A, we assess the robustness of our findings to attrition. Attrition was low, not systematic and therefore unlikely to bias the results.

[18]99 individuals out of the original sample of 3,127 were unmatched to their spouse and hence dropped.

Throughout, we report results 14 months after intervention, i.e. at Endline 2. We find insignificant treatment effects 6 months after intervention (Endline 1), which is attributable to the economic shutdown during the pandemic. (Unemployment Rate in India, CMIE).[19] Economic activity picked up following the easing of nationwide lockdown in August 2020.

4.2 Summary statistics

Table A.4 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 has 5.3 members with 19% being multi-generational (joint) families, and about 57% having a child below the age of five years. A majority of households are Hindu (82%) and over 40% of the households belong to the socio-economically disadvantaged SC-ST group. Nearly two-thirds of these households are migrants from outside Delhi but have lived at the current location for over 28 years on average.

Panel B presents the individual characteristics of the main respondents, i.e. the couple, in our sample. They are relatively young (32.7 years), with some education (over 60% have above the primary level of education) and high usage (94%) of mobile phones. Overall, 60% of them are working (irrespective of gender), out of which 16% are engaged in casual labor, 21% are self-employed and 22% have salaried jobs in government and private institutions.[20] Unemployment rate is low at 3%, while 38% of the sample is not looking for work, i.e. not in the labor force.[21] The average individual earnings was 6,028 (10,793) INR per month unconditional (conditional) on work status. Finally, Panel C summarizes the characteristics of two rank-ordered peers listed at baseline. These peers are comparable in age, education, and work status to the main respondents.

The treatment and control groups are balanced in terms of household characteristics (Appendix Table A.5) as well as individual characteristics for both husbands and wives (Appendix Table A.6), apart from marginal differences in unemployment rates. We include this and other baseline characteristics in our main specifications to account for potential pre-existing differences between treatment groups.

[19]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.

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

[21]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.

4.3 Gender differences

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

Labor market participation: The gender differences in the overall labor force participation variables are shown in Panel A of Table 1. We find significant differences in the work characteristics of husbands and wives at baseline. Wives are 72 pp less likely to be working in the reference period than their husbands. While husbands are mostly engaged in salaried jobs, the highest proportion of wives who are working is engaged in self-employment. 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 greater mismatch between expected and actual earned wages of wives compared to their husbands among our sample that registered on the job aggregator platform. Wives who registered on the platform expected an average salary of around 10,300 INR (129% higher than the average baseline earnings of women who work), while husbands expected 13,400 INR or 9% higher than their average baseline earnings. This mismatch between expected and actual earnings persists even after accounting for differences in occupational preferences and baseline occupation types of men and women, supporting our conceptual framework of women's higher reservation wage (see Appendix Table A.7).[22]

Social network structure: We also document sharp gender differences in the social network structures reported in Panel B of Table 1. First, wives' social networks are significantly more family-centric and home-bound compared to their husbands'. 96% of wives' peer networks are made up of non-coresident relatives and neighbors compared to just 56% for husbands. The narrowness of wives' networks is also reflected in a negligible proportion of them reporting any friends (defined as not a relative or neighbor) as their peers, in contrast to their husbands (4% versus 44%), and no co-workers, which is not surprising as only a quarter of wives report to be working. Second, social networks are gender-homophilous. Nearly three-fourths of

[22]Consistent with our conceptual framework showing a steeper labor supply curve for women, 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 working within a 3 km distance from their homes, on average. In contrast, men registered for a larger number of job profiles (service sector jobs (60% - delivery boy, office helper, and salesman), factory and manufacturing jobs (23% - machine operator and technicians), domestic help and services (27% - driver, peon), and construction work (10%)). They were willing to travel more than double the distance (6.6 km) preferred by women.

wives' peers are female, while more than 90% of their husbands' peers are male. Appendix Table A.8 presents further details on the composition of wives' and husbands' social networks. As Panel B reveals, on average, only around 20% of these female peers of wives are likely to be working in baseline, compared to 90% of their husbands' (overwhelmingly male) peers (Panel A). This structure of women's social network, which is likely to be less amenable to obtaining job information and referrals, intensified at intervention (Panel C). The peers suggested for treatment by wives in T2 were more likely to be female (80%), younger (by about 3 years), and 5 pp less likely to be working than peers reported at baseline. In addition, the home-bound structure continued to dominate - 85% of the treated peers were either non co-residing relatives (46%) or neighbors (39%).

Social norms and work preferences: Table 2, Panel A indicates a high prevalence of attitudes supporting traditional gender roles among both husbands and wives (asked in privacy). A vast majority of respondents support the view that women should be homemakers, although wives are slightly less than their husbands. Wives are also more likely to believe they should support their husband's career over their own, and prioritize relationships with children over market work.

In Panel B, we summarize responses to attitudes toward women's work outside of home. While neither oppose female mobility, wives are 6 pp more likely than husbands to support women's 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.[23] Note that only 2% of wives and 3% of husbands agree that women should not work, indicating demand for jobs for women. Furthermore, relatives and neighbors, who overwhelmingly comprised wives' peers in her social network, were more likely to hold regressive gender attitudes (see Appendix Table A.9).

[23]Using data on women working 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 hours per day, compared to 6.5 hours 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.

4.4 Estimation strategy

Our first empirical specification combines both treatment arms (non-network and network) into a single indicator of treatment status that takes value 1 if the couple (either with or without the wife's peers) was offered to register with the job aggregator platform, and zero otherwise. Thus, the baseline ANCOVA specification is:

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

where Y_{iv} are various labor market outcomes of individual i in cluster v at endline, including work status, the number of days worked in a month, the number of hours worked in a day, log monthly earnings, and occupation category (i.e. casual labor, self-employed or salaried).[24] Work status is a dummy variable that takes value 1 if an individual reports being engaged in an occupation over the past 3 months and zero otherwise. The occupation categories are dummy variables constructed on the basis of the main occupation in the previous quarter.[25]

T_v is a dummy variable indicating whether cluster v is randomly assigned to either treatment - non-network (T1) or 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).[26]

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

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

where T_v^1 is a dummy variable indicating whether cluster v is assigned to the couples-only i.e. non-network treatment, while T_v^2 is a dummy variable indicating whether cluster v is assigned to the couple plus the wife's peers i.e. network treatment. We interpret the coefficients on

[24] The reported number of hours worked in a day is trimmed at 14 hours due to which 15 observations are dropped (0.56% of the sample (husbands only) at Endline 2).

[25] We first asked about the main activity of an individual over the previous quarter from the time of the survey. Work status is a binary variable equal to 1 if the respondent is engaged in casual labor, self-employment or salaried work during this reference period, and zero otherwise. For this reference period, we then asked days worked in a typical month, the average number of hours worked in a day, and the monthly earnings.

[26] The estimation strategy, including the list of control variables, is as per the pre-registered analysis plan. See Table A.4 for details on the construction of the occupation and other variables, including the asset index.

the treatment variables as intention-to-treat (ITT) estimates. The control variables are the same as discussed above. In both specifications, the standard errors are clustered by the unit of randomization, i.e. the polling station (PS).

5 Main results

5.1 Labor market participation

Table 3 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).[27]

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 either treatment group relative to the control group. Note that the point estimate for the non-network treatment group is negative while that for the network treatment group is positive, and significantly higher than in the non-network treatment group (p=0.02). In contrast, we find a significant improvement in the husbands' likelihood of working in the network treatment group by 4.4 percentage points (pp) relative to the control group (equivalent to 4.6% of the baseline mean). Similar to their wives, the coefficient for husbands in the network treatment group is also significantly higher than that for their non-network treatment counterparts (p=0.00).[28] The coefficients for wives are not significantly different from husbands for overall treatment or T1 and T2.

Next, we examine the treatment effects on the intensive margin in Table 4, measured by the number of days worked in a month (Panel A) and the hours worked in a day (Panel B).[29] Wives show a negative but insignificant overall treatment effect on both dimensions of the intensive margin (Panels A and B, column (1)). However, disaggregating by treatment type, we note a significant reduction on both dimensions for wives (Panels A and B, column(3)) in the non-network treatment group (T1) but not in the network treatment group (T2).

[27] Appendix Table A.10 shows insignificant effects 6 months after intervention (Endline 1), attributable to the economic shutdown during the pandemic.

[28] We also analyze the heterogeneity in these treatment effects by baseline demographic characteristics in Appendix Table A.11. We find no statistically significant difference in the outcomes of wives or husbands in the network treatment group by poverty status, caste, religion, education (own or spouse), and having young children (aged 5 or below). However, the treatment effect of a higher employment rate is driven by the relatively younger husbands (aged 15-30 years) in T2 with no significant effect on husbands aged 30-45 years.

[29] We also test for alternative log specifications - IHS transformation ($log(y) = log(y+(y^2+1)^{1/2})$ (Burbidge *et al.*, 1988)) and taking logs after adding a small positive value of 0.01 to account for zero values, which yields qualitatively similar results.

In contrast, we find positive and significant overall treatment effects on the monthly workdays of husbands (Panel A, column (2)), as well as positive, though insignificant, overall treatment effects on their work hours (Panel B, column (2)). Husbands in both the treatment arms reported increased number of days worked in a month (Panel A, column(4)). In the non-network treatment group it increased by 1.5 days (6.76% of sample mean) while in the network treatment group the magnitude was higher (but not significantly different) at 1.9 workdays (8.36% of sample mean). The coefficients for wives are significantly different from their husbands at 10% significance level for the overall *Treatment* (p= 0.01), as well as in T1 (p< 0.001) and T2 (p= 0.09).

We find a positive, though insignificant, overall treatment effect on work hours of husbands (Panel B, column (2)) but there was a significant (p<0.10) difference across the two treatment arms (Panel B, column (4)). The hours worked per day by husbands in the network treatment arm went up by 0.66 (8.11% of sample mean) with no effect in T1. For work hours also, the coefficients for wives are significantly different from their husbands at 10% level of significance for the overall *Treatment* (p= 0.06), as well as T1 (p= 0.09) and T2 (p= 0.07).

5.2 Occupational choice and Earnings

We also examine the impact of the intervention on the type of work (self-employed, salaried, or casual labor) in order to test for occupational shifts in Table 5. We find that, while wives experienced no significant overall treatment impact on their work status as reported in Table 3, their self-employment in the network treatment group increased by 4.5 pp (column (3) of Table 5). This appears to be accompanied by a reduction, though insignificant, in their engagement in causal labor (column (11), p>0.10), indicating a substitution away from precarious work for wives in the network treatment group. We find a similar movement away from casual labor for the non-network treatment group wives (p<0.10), but a concomitant shift to self-employment is absent (column (3), coefficient on T1), consistent with the negative point estimate for overall employment for this group of wives in Table 3. This may also be a key factor driving the reduction in the work days and work hours of the non-network group, as reported in Table 4. There is no significant impact in terms of salaried jobs for women (columns (5) and (7)) in either treatment arm. Husbands too appear to be substituting away from casual work (column (12)) into better, salaried jobs and self-employment, though imprecisely estimated.[30]

Next, we examine whether the observed impact on labor force participation and occupational

[30]Note that there is insignificant gender differential in salaried or casual work in both treatment groups, while for self-employment there is a significant difference between wives and husbands in T1 only (p= 0.06)

change affected monthly (individual) earnings, as reported in Table 6.[31] The overall treatment effect for wives is negative though insignificant (column (1)), driven by the fact that the non-network treatment wives experienced a contraction in their earnings relative to the control group (column (3), $p<0.10$), consistent with their withdrawal from casual labor discussed earlier. In contrast, their network treatment counterparts were successful in avoiding such contraction to their earnings: the estimated coefficient is positive and 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 earnings more than doubled relative to the control group (column (4) of Table 6).

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

Our ITT estimates are robust to concerns about multiple hypothesis testing (Tables A.13 and A.14). Given the low platform registration rates (about 25% amongst main respondents and 35% amongst treated peers), we also instrument for registration on the portal with random assignment to treatment (either T1 or T2) to obtain treatment on treated (TOT) estimates.[32] Our findings are similar (Appendix Table A.15): we find an insignificant impact on registered wives' work outcomes with a larger estimate on workdays ($\sim$6.1, $p<0.05$) and monthly earnings (=3.3, $p<0.05$) of registered husbands. The impact on the work status of registered husbands (wives) is positive (negative) and close to the ITT effect of T2 at 4.2 pp but imprecisely estimated ($p>0.10$) as in Table 3 above.

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

[32] We use the same set of control variables and cluster standard errors at the PS level as in the main specification.

To summarize, while wives' labor market participation or earnings did not improve significantly in either treatment group, we find an increase in the likelihood of self-employment among wives in the network treatment group.[33] In contrast, we observe a marginal decline in women's work intensity (and hence, earnings) in the non-network treatment group, driven by a reduction in casual work. Furthermore, we find that husbands' probability of working, intensity of work, and earnings increased in the network treatment group, while their non-network treatment counterparts experienced gains on the intensive, but not extensive, margin of work or earnings. These findings are robust to concerns about attrition (Appendix Tables A.16 and A.17).

6 Mechanisms and Discussion

In this section, we relate our experimental findings to our conceptual framework in Section 2 to explain the potential mechanisms underlying the various estimated treatment effects for wives and husbands.

To recapitulate, our conceptual framework posits that introducing the job aggregator platform to the couple implies that higher household income from increased job offers (via a shift in J_f) carrying greater compensating differential in wages for wives may offset the loss in terms of non-conformism to the norm for women's work OOH $\bar{e}_f$, thereby boosting female labor force participation.

However, as job opportunities simultaneously improve for husbands due to the job aggregator (i.e. J_m shifts too), they might be more likely to take up these better jobs (or work longer) owing to their lower reservation wage compared to wives in the range $e_f \geq \bar{e}_f^k$ (i.e. where the norm constraints are binding). This limits the positive impact of the job aggregator on wives' OOH work (in the non-network treatment), as wives have to spend more time in home production H to compensate for higher OOH work by men. In other words, women now have a smaller set of acceptable jobs making a match more difficult, as illustrated in Figure 1. Thus, the extra norm constraint on wives' OOH work can undo the potential positive impact of job aggregator platform on female employment.

Our experimental results are consistent with this explanation, showing that while access to the job aggregator platform may have helped in smoothing some of the job search constraints faced by wives, it was not sufficient to overcome the burden of domestic work and the norms constraints faced by them. Specifically, although women did receive job offers, these did not come with a high enough compensating differential for wives to justify deviating from the norm. This is consistent with the fact that wives' expected or reservation wages are

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

consistently much higher than the market wages for their preferred job types relative to men, as shown in Appendix Table A.7, and discussed previously.[34] To this extent, these results augment the emerging literature on the role of overly optimistic worker beliefs about their job prospects in explaining employment outcomes (Banerjee & Sequeira, 2023; Abebe *et al.*, 2020; Kelley *et al.*, 2022), by highlighting the gender differences in the implications of such mismatched beliefs.

Thus, despite the theoretical possibility that lowering job search costs for women can increase female employment, our findings indicate that existing norms constraints, combined with the externality imposed by husbands working more intensively, may dampen such positive effects in the non-network treatment, due to the household optimization problem. This explains why female employment falls in the short run, both at the extensive (Table 3) and intensive margins (Table 4), as women withdraw from precarious work (casual wage labor) to wait for the arrival of better-suited job offers from the platform (see Table 5).

The fall back option for many wives in our setting is self-employment, which satisfies the norm constraint but pays less.[35] However, since it is costly to set up a business, the household will decide whether the woman should engage in self-employment only after a significant search in the labor market has been conducted, to obtain the best estimate of the "true" J_f. In the non-network treatment group, an individual wife will only have her own information on job opportunities that she received within the stipulated period, that may not yet have been enough to stop searching and move into self-employment.

In contrast, in the network treatment group, a similar reduction in casual employment is accompanied by a concomitant increase in self-employment among wives, driven by an increase in their engagement in own business manufacturing activity (see Appendix Table A.18) - primarily home-based work, such as tailoring. Communication with other treated (female) peers in the network may have enabled wives in the network treatment group to arrive at a better estimate of the true J_f faster, leading wives to relinquish the search for suitable jobs earlier and move into self-employment. Wives may also update their estimate of the true J_f based on peers' employment status: higher self employment among peers may lead wives to infer that it is not worth waiting for better jobs to arrive. This explanation is supported by our finding that the self-employment effect of wives in the network treatment group is driven by those wives whose treated female peers also took up self-employment

[34] Appendix Table A.7 shows the percentage gap between expected and actual wages for different types of jobs offered on the HNM portal for women (col 3), only working women who are likely to be better informed about market wages (col 6) and men (col 9). Although we do not have out-of-sample actual market wages for each job category, these data are suggestive of much larger misalignment in reservation wages versus market wages for women.

[35] Appendix Table A.18 shows that self employment among wives is mainly in own business manufacturing.

contemporaneously (see column (2) in Appendix Table A.19).

Furthermore, our conceptual framework outlines how the conservative network structure of wives in the network treatment group might explain the null effects on their employment. To recapitulate, our model posits that home-bound, conservative network structures might reinforce patriarchal norms to keep wives' outside work low, while friends-based, liberal networks may encourage challenging the existing low norm. We test this explanation by exploring heterogeneous treatment effects for employment along two dimensions:

(a) *type of peers in baseline*: we find that network treatment wives without family members in their social network are 16 pp (p<0.05) more likely to be working relative to control, but this effect is completely reversed for those whose peer network includes relatives (column (1), Table 7). Furthermore, network treatment wives whose peer networks consist of more friends are also more likely to work. Taken together, these results confirm that family-based networks have a negative effect on wives' employment while friend-based networks have the opposite effect.[36] No such heterogeneity is observed for husbands.

(b) *peers' reported attitudes*: we find that network treatment wives whose peers reported relatively progressive (conservative) attitudes at baseline are more (less) likely to be working relative to the control group (columns (5) and (7), Table 8). In summary, these results suggest that the structure of the wives' social network constrained their labor market outcomes, either by making them conform to existing norm of low employment or via fewer weak ties (Calvo-Armengol & Jackson, 2004; Mortensen & Vishwanath, 1994)), or both. Furthermore, while access to the platform (both with and without network) attenuated regressive attitudes towards gender roles, it failed to amplify progressive attitudes around women's work (discussed further in Section 6.1 below), highlighting the stickiness of such norms and the inherent challenges faced in changing them.

Turning now to husbands, we find that in the non-network treatment group, husbands' intensive margin of work increased. Since most husbands are already employed at baseline, this is consistent with the non-network treatment husbands taking up better jobs than before. In contrast, we find the network treatment husbands enjoy positive employment effects at both the extensive and intensive margins. Our theoretical model indicates that the overlapping nature of spouses' respective social networks through common family members and neighbors may be driving this effect, particularly for unemployed wives. In other words, alongside reinforcing the existing norm of low employment among the wives as discussed above, home-bound networks of wives may also benefit their husbands by passing on relevant job information, leading to increased job offers and better employment outcomes for those

[36] We use the word 'effect' for ease of exposition, but we cannot make causal claims here since network structure is endogenous.

husbands.

We directly test this network-based explanation by examining whether the husband's employment varies by the overlap with his wife's network. Husbands in the network treatment who shared their social network with wives (at baseline) were indeed more likely to be employed one year after the intervention (Table 9, columns (2) and (4)). The presence of non co-residing relatives and neighbors in the wife's social network (at baseline) significantly increases the probability that the husband is working at endline. This is also consistent with our within-treatment analysis that conditional (unconditional) on interest in registering on the portal, husbands in the network treatment group were 15 (5.2) pp more likely to receive job offers as shown in Table A.22, columns (2) and (4), and received 0.20 additional job offers (column 6), compared to their counterparts in the non-network treatment group. However, this was not the case for wives (columns (1) and (3)).[37] Of the 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. Consistent with this explanation, we find significant positive impacts only on T2 wives' male peers' employment outcomes (both extensive and intensive) but not on their female peers, as shown in Appendix Table A.20.

6.1 Alternative explanations

In this section, we attempt to rule out other possible explanations for our results, beyond that posited by our theoretical model. We focus on four key such alternative mechanisms below. Several others are discussed in greater detail in Appendix C.

First, are women less likely to take up new digital technology resulting in gender-differentiated treatment effects? As Appendix Table A.21 shows, there is no statistically significant gender difference in the take-up of the technology as measured by registration on the platform, whether unconditional or conditional.[38] Of course, both wives and husbands have higher platform registration rates in the network treatment group relative to the non-network group, consistent with positive peer effects in take-up, but we find no statistically significant gender differences therein. Moreover, the design feature of the platform that matches workers with employers (and hence jobs) based on their elicited preferences addresses another potential explanation that women don't want to work in these jobs and hence didn't take them up.

[37] While this analysis uses self-reported data on job offers as described in Section 4.1, the portal data also corroborates these survey findings.

[38] Furthermore, since registration could be completed by just having a simple phone, we check for, but do not find, any heterogeneity in our results by mobile phone ownership or usage of the respondent.

Second, was there insufficient demand for women's labor, especially in the context of potentially systematic gender differences in the recovery of the labor market during the post-pandemic period, that might explain the null effect on women's employment? In other words, did women's employment not increase because there were just no jobs for women? The descriptive evidence appears to belie this concern. First, the bottom two rows in Appendix Table A.22 indicate that the (unconditional) job offer rate for wives was similar (if not marginally higher) to that of their husbands (9% compared to 7%) in the placebo group, i.e. the non-network group. Second, looking at the broader time trends of female labor force participation in Delhi and urban India post-pandemic (see Appendix Figure A.2), we find that female employment rates had already begun to recover from losses during the pandemic around the time of our endline in 2021, indicating the potential of digital job search platforms in further boosting demand for women's labor at this time.

Third, could the increase in employment rates of husbands in the network treatment group be driven by a recovery response to sharp male job losses during the pandemic? However, we find no differential employment outcomes for husbands in the network treatment group, either by job loss during the pandemic or work status right after the pandemic-induced lockdown at Endline 1 (results available on request). Thus, husbands in the network treatment group 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.

Finally, we do not find any evidence of differential impacts of the two treatments on gender norms driving our results. We report the estimated effect of treatment (using our main specification) on indexes of attitudes towards gender roles and women's outside work in Table 10.[39] Treatment reduces the index of regressive gender attitudes by almost 0.2 SD for wives and husbands (columns (1) and (2)), compared to the control group. This is not statistically different between treatment groups for both sexes (columns (3) and (4)). While we do not find a strengthening of the progressive attitudes towards women working outside the home, wives in T1 exhibit a more positive attitude (column (5)) but this effect does not differ across the two treatments (column (7)). Moreover, there is a null effect of treatment on the attitudes of husbands toward women's outside work. Clearly, access to technology has the potential to increase the perceived returns to wives' work by weakening regressive gender norms. But being treated with the network has no differential effect on these attitudes, strengthening our proposed mechanism of greater flow of job information from peers in the network treatment that benefited husbands, but not their wives.

[39] See notes to Table 10 for details on the construction of the indices. For the disaggregated impact of treatment on gender attitudes by each component of the indexes see Appendix Tables A.23 and A.24.

7 Conclusion

In this paper, we study the impact of offering new job search technology aimed at lowering labor market frictions to married couples, either on their own or alongside the wife's social network. While overall labor force participation of wives remain unaffected in either treatment group compared to control group, self-employment improved among wives who were treated alongside their peers but intensity of work declined among those who were treated alone. Furthermore, husbands in the network treatment group enjoyed significant gains in labor force participation, work intensity and earnings. We argue that the home-bound nature of women's social networks reinforce existing norms of low female (outside) employment to keep wives at home, while simultaneously benefiting their husbands (owing to significant network overlap) through labor market information sharing. Existing research has identified social networks as an important positive driver in the adoption of new technology (Beaman *et al.*, 2021; Bandiera & Rasul, 2006). However, our findings shed new light on how the structure of social networks can moderate the impact of new technology, differently for men relative to women, in the context of labor markets in developing countries. Indeed, we show that the nature of social networks are important not only in job search but also in challenging (or lack thereof) gender norms.

While employment need not necessarily guarantee improved well-being, women's engagement in paid work is important for both equity and growth reasons, particularly in a country like India with historically and stubbornly low labor force participation among women. Hence, our findings have implications for the development of effective interventions to expand women's networks beyond the boundary of their families to improve their labor market outcomes and overall economic well-being, indicating a promising area for further research.

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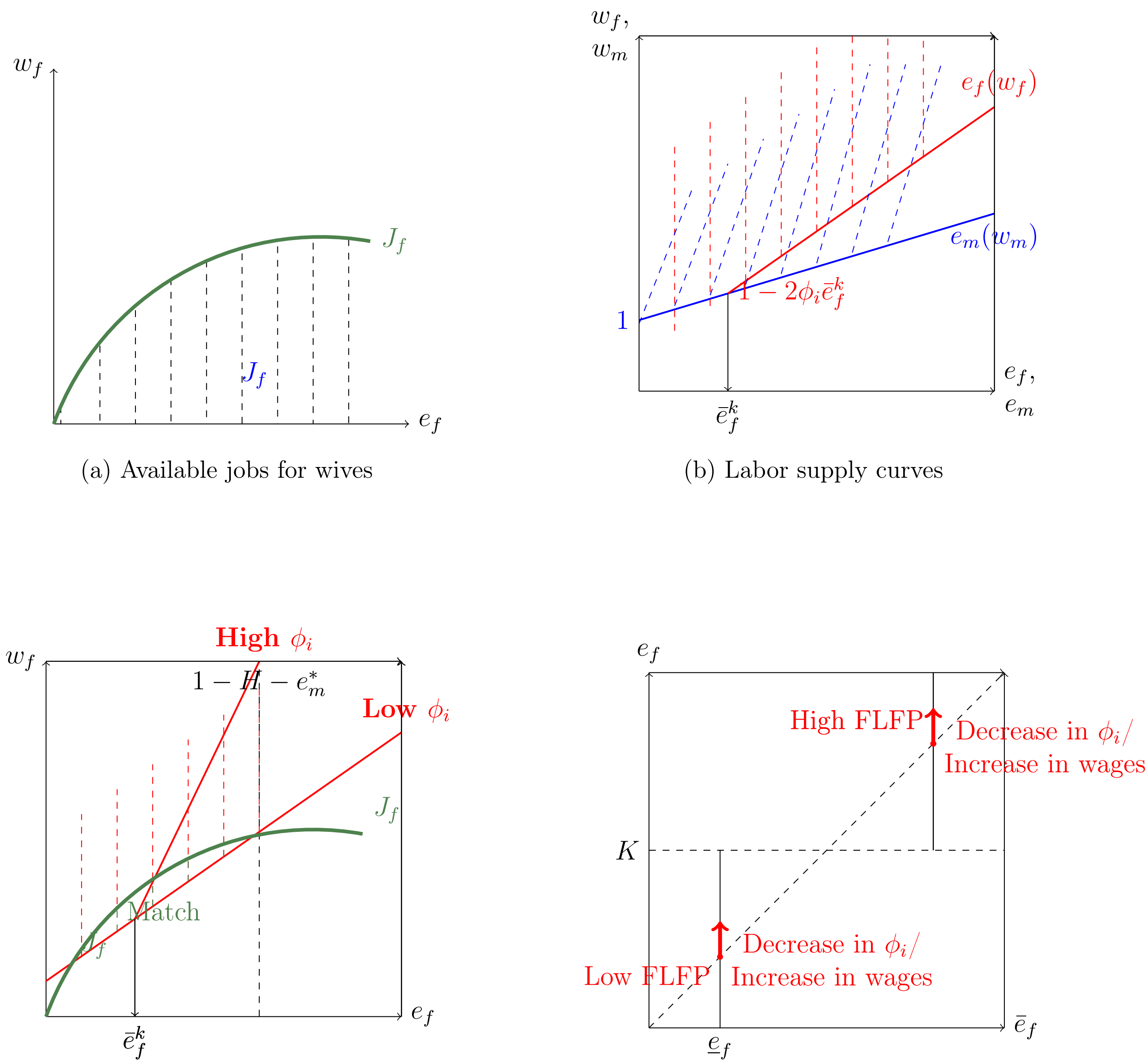
Figure 1: Conceptual framework



(a) Available jobs for wives

(b) Labor supply curves

(c) Matches when ϕ_i is high vs low

(d) Multiple equilibria

Table 1: 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)	
Expected earnings (INR)	10246.77	13384.25	-3137.48***
	(214.91)	(309.91)	
	Panel B: Social Network (by relationship and gender)		
Non co-resident relative	0.75	0.39	0.35***
	(0.30)	(0.37)	
Friend	0.04	0.37	-0.33***
	(0.12)	(0.37)	
Neighbor	0.21	0.17	0.04***
	(0.29)	(0.27)	
Co-worker	0.00	0.07	-0.06***
	(0.04)	(0.18)	
Female	72.06	12.38	59.68***
	(0.25)	(0.21)	
N	1514	1514	

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

Table 2: Attitudes and preferences towards women's work, by gender (at baseline)

	Wife (1)	Husband (2)	Wife - Husband (3)
Panel A: Attitude towards gender roles			
Woman should take care of home	0.8	0.88	-0.078***
	(0.4)	(0.33)	
Woman should support husband's career	0.86	0.73	0.13***
	(0.34)	(0.44)	
If mother works children suffer	0.88	0.88	0.00
	(0.33)	(0.33)	
If mother works poor relationship with children	0.36	0.3	0.06***
	(0.48)	(0.46)	
N	1513	1510	
Panel B: Attitude towards women's outside work			
Woman can travel outside locality	0.88	0.88	-0.01
	(0.33)	(0.33)	
Woman can work outside home	0.91	0.84	0.06***
	(0.29)	(0.36)	
Woman can work even if husband provides	0.6	0.33	0.27***
	(0.49)	(0.47)	
If woman works husband shares domestic duties	0.95	0.97	-0.025***
	(0.22)	(0.16)	
N	1513	1506	
Panel C: Job preferences for women			
Salaried	0.67	0.78	-0.10***
	(0.47)	(0.42)	
Casual	0.08	0.03	0.05***
	(0.27)	(0.18)	
Domestic help	0.02	0.01	0.01***
	(0.15)	(0.09)	
Home-based	0.81	0.78	0.03**
	(0.39)	(0.41)	
Should not work	0.02	0.03	-0.10**
	(0.13)	(0.17)	
N	1514	1514	

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

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

Note: The dependent variable in Panel A (B) is the average number of days worked in a month (the number of hours worked in a day) in the reference period. Days worked in a month were calculated by multiplying the number of days worked in a week by four. In Panel B, we drop the outliers where the number of hours reported were above 14 per day. Columns (1)-(2) report the combined treatment effect using equation (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). In Panel A and B, 'Mean Y' denotes the mean value of workdays and work hours, respectively, for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: 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 6: 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 7: Heterogeneity in the impact of treatment on work status by structure of network ($>$ 1 year after intervention)

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

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

Table 8: The impact of treatment on own work status by peers' gender attitudes

(> 1 year after intervention)

	Regressive gender roles		Progressive work attitudes	
	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)
T1 (without network)	-0.048	-0.019	-0.084**	-0.005
	(0.031)	(0.038)	(0.038)	(0.028)
T2 (with network)	0.089**	0.064*	-0.052	0.048*
	(0.042)	(0.033)	(0.038)	(0.027)
T1 x Z	-0.011	0.002	0.056	-0.038
	(0.057)	(0.058)	(0.047)	(0.055)
T2 x Z	-0.125**	-0.034	0.150***	-0.003
	(0.061)	(0.043)	(0.046)	(0.039)
Observations	1,016	1,011	1,016	1,012
R-squared	0.199	0.058	0.200	0.057
Estimate T1 (Z=1)	-0.059	-0.017	-0.027	-0.043
Estimate T2 (Z=1)	-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. The average over 'Peers' attitudes are measured at baseline. *Regressive gender roles* indicates relatively restrictive gender attitudes (takes a value of one for above median Z-score of regressive attitudes and is zero below median values) and *Progressive work attitudes* indicates relatively liberal attitudes towards women's outside work (takes a value of one for above median Z-score of progressive attitudes and is zero below median values). For our main categories ($Z = 1$), these characteristics equal one and zero for the base categories ($Z = 0$). The first two rows report the regression coefficients for T1 and T2 for the base categories while the third and fourth row report the heterogeneous treatment effects for T1 and T2, respectively, by these characteristics. The last two rows 'Estimate (Z=1)' report the estimated coefficients for the main categories for T1 and T2, respectively. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Standard errors clustered at PS level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: Heterogeneity in the impact of treatment on work status by network overlap

(> 1 year after intervention)

	Relatives/Neighbors		Friends	
	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)
T1 (without network)	-0.043	-0.018	-0.043	-0.018
	(0.027)	(0.020)	(0.027)	(0.020)
T2 $\times Overlap = 0$	0.008	0.033	0.016	0.043**
	(0.029)	(0.021)	(0.030)	(0.020)
T2 $\times Overlap = 1$	0.050	0.073***	0.407	0.085***
	(0.051)	(0.020)	(0.256)	(0.028)
p-value [*Overlap*]	[0.35]	[0.03]	[0.13]	[0.13]
Observations	1,377	1,377	1,377	1,377
R-squared	0.182	0.054	0.184	0.053

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

Table 10: Impact of treatment on own gender attitudes (> 1 year after intervention)

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

Note: The dependent variables are Attitude Indices created by taking an equal weighted average of the standardised Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the responses to questions on gender attitudes. In columns(1)-(4), we have Index of attitudes towards gender roles that is constructed using responses to - (1) It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family, (2) It is more important for a wife to help her husband's career than to have one herself, (3) When a mother works for pay, the children suffer, (4) A working mother cannot establish just as warm and secure a relationship with her children as a mother who does not work. And in columns (5)-(8), the Index of attitudes towards women's outside work is weighted average of the responses to the following questions - (1) In your opinion, is it acceptable for an adult woman to travel outside the locality if she wants to?, (2) In your opinion, should an adult woman work outside of home if she wants to?, (3) Do you approve of a married woman earning money if she has a husband capable of supporting her? and (4) In your opinion, if the wife is working outside the home, should the husband help her with household/care duties? Columns (1)-(2) and (5)-(6) report the combined treatment effect using equation (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

A Sampling and Attrition

We use publicly available household listing from electoral registers as the basis of our sampling frame. Delhi has over 300 Electoral Board (EB) wards contained in 70 Assembly Constituencies (AC) across 11 districts.

EB wards where the largest proportion of households consisted of slum clusters (low-income residential areas) resettled into permanent habitations were considered for sampling and mapped into relevant Census 2011 wards to assess their population, employment, literacy, and civic amenities. We sampled 24 such EB wards spread across 11 ACs within 5 districts of Delhi - West, North, North-west, Shahadra, and North-east. On average, an AC consists of around 150-180 polling stations (PS), with approx. 500-1000 eligible voters (or 250-500 households) per PS. For each of the 11 sampled AC, a stratified random sample of about 10 PS was drawn, and within each sampled PS, 15 households were randomly sampled for inclusion in our study. Stratification of PS was by proportion of low-income residential households. 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. A household was considered eligible for the study if it had at least one married couple in the age group of 18-45 years. Figure A.1 shows the geographical spread across Delhi of the sampled 108 polling stations, which form our primary sampling unit (cluster)

As mentioned in Section 4, attrition is negligible in our data (below 5%).[40] 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.16 show that our results remain unchanged. We continue to find that the probability of working, the intensity of work (workdays and work hours), and earnings in the network treatment group for husbands is higher relative to the control group. The higher beneficial effect in T2 (network treatment) over T1 holds for both husbands and their wives.[41]

[40] At both Endline 1 and Endline 2, the attrition rates were comparable across the three groups. At Endline 1, the attrition rates were 3% for T1, 1.5% for T2, and 1% for the control group. At Endline 2, the rates were 4.5% for T1, 7.5% for T2, and 2.5% for the control group. Notably, the baseline characteristics, such as age, education, and employment status, of those who dropped out were similar to those who remained in the sample.

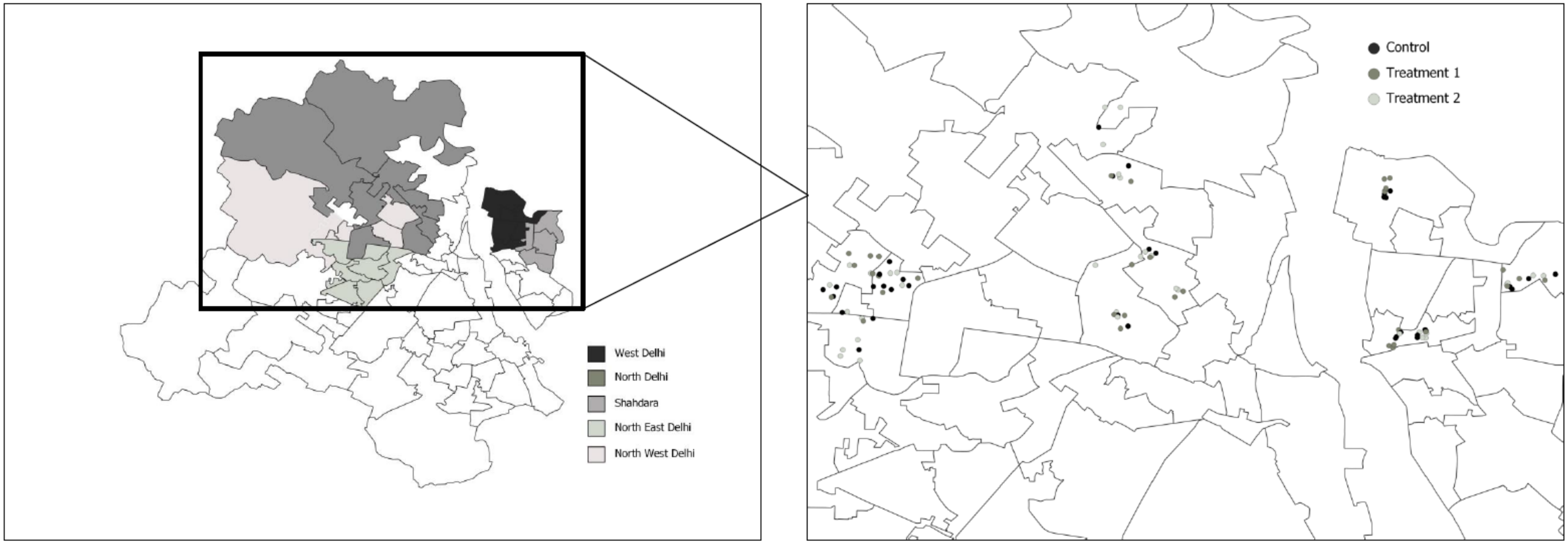
[41] The attrition rates for the peers were comparable in T1 and control groups, while T2 exhibited a relatively higher attrition rate. At Endline 1, the attrition rate was 11% for both the T1 and the control

Furthermore, we follow Ghanem *et al.* (2021) to test for attrition bias in our sample. For this, we test for the differences in mean baseline outcomes across the treatment arms for the non-attriters and the attriters. Appendix Table A.17 reports the baseline mean for two main outcome variables: (i) work status (Panel A), and (ii) average monthly earnings (Panel B). Columns (1)-(3) report the mean for the non-attriters while columns (4)-(6) report it for the attriters. In columns (7)-(8), we report the p-values of the test of mean differences between the treatments and control group for the non-attriters, while the corresponding p-values for attriters are in columns (9)-(10). We find that both these baseline outcomes are similar across control and treated non-attriters in both the treatment arms (columns (7)-(8)) as well as treated and control group attriters (columns (9)-(10)). Additionally, there are no significant differences in both these outcome variables amongst all treatment-response subgroups, i.e. between the treatment and control respondents and attriters. Therefore, the difference in mean outcomes at endline identifies the treatment effect on our sample since the identifying assumption of internal validity is satisfied.[42]

group and 20% for T2. And at Endline 2, the attrition rate ranged from 14-15% for T1 and the control group, whereas it was 18.5% for T2. At both endlines, the age and education level of surveyed peers are similar to the peers who drop out of the sample but the former have a lower baseline employment rate compared to the latter (63% vs 69% at Endline 1 and 62.5% vs 71% at Endline 2, respectively.)

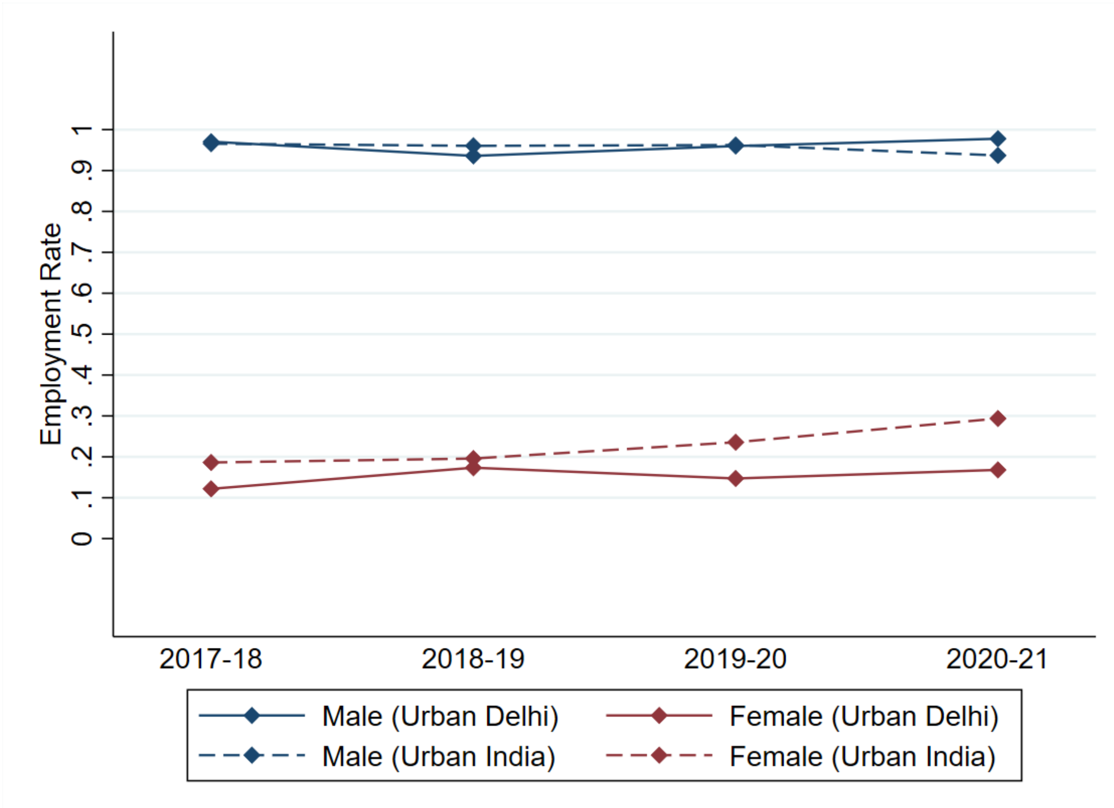
[42]We also carried out the standard inverse-probability weighted (IPW) approach. Our results are robust to correction for selection on observed household and individual characteristics as well as multiple hypotheses tests.

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



B Additional Figures and Tables

Figure A.2: Employment trends by gender



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

Table A.1: Registrations on HNM job portal, by occupation and gender

Job Profiles	Worker registrations			Featured for job opening			Called for job	
	All (1)	Female (2)	Distance (3)	All (4)	Female (5)	Distance (6)	All (7)	Female (8)
Overall	**64649**	**0.57**	**5.37**	**9364**	**0.80**	**2.74**	**6047**	**0.80**
Babysitter	1420	1.00	3.05	710	1.00	2.74	469	1.00
Beautician	556	0.93	4.23	42	1.00	6.77	27	1.00
Cook	2748	0.88	3.54	3079	0.87	2.31	2021	0.87
Driver	3110	0.00	9.12	881	0.00	5.25	550	0.00
Maid/domestic helper	15613	0.88	3.54	4249	0.94	2.34	2712	0.95
Medicinal Helper	461	0.57	5.92					
Office Helper	22037	0.38	6.40	203	0.20	3.75	125	0.12
Other	909	0.06	8.55	12	0.00	7.86	7	0.00
Other Helper	11180	0.70	4.52	55	0.31	3.92	38	0.21
Other Technician	1243	0.03	8.54	4	0.00	3.76	4	0.00
Salesperson	5372	0.42	6.41	129	0.02	5.20	94	0.00

Note: We summarise the job profiles of the universe of workers registered on the HNM portal till December 2019 and the job profiles for which they were 'featured' or listed for employers and (phone) called by employers, again upto December 2019. Columns (1)-(3) list the preferences of registered workers - the total number of job profiles workers registered for (column (1)), the proportion of women in the total works registered (column (2)), and the distance they are willing to travel (in km) (column (3)). Columns (4)-(6) record the number of workers who were featured for each job (column (4)), the proportion of women featured for each job (column (5)), and the average distance of the worker from employer (column (6)). Lastly, columns (7)-(8) list the number of workers who were called (column (7)) for the featured job and the proportion of women called for that jobs (column (8)). *Other* includes job profiles of skilled construction worker/mason, Machine Operator, Bartender, Supervisor. *Other Helper* includes Salon Helper, Stitching Helper, Security Guard. And *Other Technician* comprises Construction Painter, Electronic Technician, Construction Carpenter, Construction Plumber.

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

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

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

Table A.3: 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 A.4: 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 A.5: Balance of household characteristics (at baseline)

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

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

Table A.6: Balance of individual characteristics (at baseline)

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

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

Table A.7: Mis-match in the expected and actual salaries (in INR)

Job Profiles	Women			Working Women			Men		
	Expected salary (1)	Actual salary (2)	Mismatch (%) (3)	Expected salary (4)	Actual salary (5)	Mismatch (%) (6)	Expected salary (7)	Actual salary (8)	Mismatch (%) (9)
Overall	8637.24	4183.12	106.48	8005.19	5047.35	58.60	12808.61	10437.23	22.72
Babysitter	13174.07			13625.48					
Beautician	12291.37	3400.00	261.51	12731.88	3400.00	274.47	12291.37		
Cook	8537.49	5600.00	52.46	8525.30	5600.00	52.24	8537.49	5600.00	52.46
Driver	17740.42	11600.00	52.93	17986.19	11600.00	55.05	17740.42	11600.00	52.93
Maid/domestic helper	6726.03	7161.93	-6.09	6649.57	7260.51	-8.41	6726.03	7161.93	-6.09
Medicinal Helper	13271.74			14164.43			13271.74	11500.00	15.41
Office Helper	11352.87	9576.65	18.55	12461.06	9717.11	28.24	11352.87	9576.65	18.55
Other	15584.93			14287.63			15584.93	9533.33	63.48
Other Helper	10340.00	6618.17	56.24	10935.82	7282.35	50.17	10340.00	6618.17	56.24
Other Technician	11046.62			11750.20			11046.62	11451.61	-3.54
Salesperson	12049.80	10604.84	13.63	13557.44	11212.50	20.91	12049.80	10604.84	13.63

Note: The table summarizes the *Expected salaries*, *Actual salaries*, and *Mis-match* for women (Columns (1)-(3)), currently employed women (Columns (4)-(6)) and men (Columns (7)-(9)) registered on the HNM job portal. There were 25,269 women (of which 14,872 are working women) and 25,285 men registered on the portal. As a person can register for multiple job profiles, this gave us a total sample of 44,509 women, 25,108 working women, and 41,602 men. *Expected salaries* record the stated salaries the job seekers registered on the HNM portal were expecting for each job profile. The corresponding *Actual salary* for a job profile is measured as the mean salary earned by employed individuals who registered on the job portal for this job profile. Columns (2) and (5) reports the mean salaries for employed women (122 observations) and Column (8) reports it for men (363 observations). If we have no registered woman/man working in a profile the corresponding actual salaries have been left blank. *Mis-match* is the percentage deviation of expected salaries from the actual salaries.

Table A.8: Structure of social network by gender of main respondent

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

Note: Panels A and B report the type of relationship of the top two rank-ordered peers of the husband and the wife surveyed at baseline, respectively. In Panel C, the sample is restricted to the two treated (and surveyed) peers of wives only in the T2 group. This includes all peers recommended by the wives in T2 for treatment, including those reported at baseline. Of the 881 individuals (peers) suggested by wives at intervention in T2, 153 had been recommended at baseline too. The network characteristics in Panel C are reported at intervention, approximately 3-6 months after the baseline. Panels A, B, and C are based on the network data for 1198 husbands, 1123 wives (all arms) and 420 wives in T2, respectively. Standard errors in parentheses.

Table A.9: Peers' gender attitudes (at baseline)

Peers	Wive's peers			Husband's peers		
	Relative/ Neighbors	Friends	Difference	Relative/ Neighbors	Friends	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Attitude towards gender roles						
Woman should take care of home	0.831	0.6	0.23***	0.817	0.799	0.01
	(0.37)	(0.49)		(0.39)	(0.4)	
Woman should support husband's career	0.9	0.8	0.1**	0.875	0.833	0.04**
	(0.3)	(0.4)		(0.33)	(0.37)	
If mother works children suffer	0.872	0.78	0.09*	0.816	0.838	-0.02
	(0.33)	(0.42)		(0.39)	(0.37)	
If mother works poor relationship with children	0.599	0.489	0.13	0.577	0.56	0.01
	(0.49)	(0.51)		(0.49)	(0.5)	
N	1544	47		1004	670	
Panel B: Attitude towards women's outside work						
Woman can travel outside locality	0.616	0.92	-0.3***	0.659	0.696	-0.03
	(0.49)	(0.27)		(0.47)	(0.46)	
Woman can work outside home	0.82	0.9	0.15	0.778	0.809	-0.03
	(0.38)	(0.3)		(0.42)	(0.39)	
Woman can work even if husband provides	0.333	0.54	-0.21***	0.28	0.309	-0.029
	(0.47)	(0.5)		(0.45)	(0.46)	
If woman works husband shares domestic duties	0.956	1	-0.04	0.982	0.977	0.005
	(0.21)	(0)		(0.13)	(0.15)	
N	1543	47		1003	669	

Note: In Panels A and B, each row is an indicator variable that takes value one if the peer 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? Columns (1)-(2) report the average attitudes of wives' peers who are no-co-residing relatives or neighbors and friends, respectively, followed by the difference in the two estimates (column (3)). Similarly, for husbands' peers, columns (4) and (5) report the average attitudes of relatives or neighbors and friends in the social network, respectively, followed by the difference in the two estimates (column (6)) (*** p<0.01, ** p<0.05, * p<0.1).

Table A.10: Impact of treatment on labor market outcomes (6 months after intervention)

	Work Status		Workdays (per month)		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	0.379	0.735	0.060	-0.165	0.157	-0.790*
	(0.022)	(0.030)	(0.532)	(0.755)	(0.158)	(0.291)	(0.273)	(0.428)
T2 (with network)	0.015	-0.011	0.512	0.515	-0.123	-0.107	0.105	-0.187
	(0.019)	(0.027)	(0.482)	(0.709)	(0.126)	(0.293)	(0.245)	(0.406)
Baseline Y	0.341	0.338*	0.186***	0.164***	0.317***	0.154***	0.279***	0.151***
	(0.359)	(0.180)	(0.044)	(0.056)	(0.062)	(0.042)	(0.053)	(0.055)
p-value [T1=T2]	[0.51]	[0.51]	[0.8]	[0.79]	[0.24]	[0.85]	[0.84]	[0.14]
Observations	1,401	1,402	1,401	1,402	1,400	1,388	1,401	1,402
R-squared	0.156	0.047	0.152	0.049	0.196	0.046	0.179	0.050
Mean Y	0.23	0.94	5	22.75	1.05	8.15	889.07	11515.43

Note: The dependent variable in columns (1)-(2) is an indicator variable that takes a value of one if an individual is working in the reference period and zero otherwise. In columns (3)-(4) and (5)-(6) the dependent variable is the number of days worked in a month and the number of hours worked in a day, respectively. In columns (7)-(8) the outcome is the log transformation of the monthly earnings in the reference period. The p-values correspond to the test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the corresponding dependent variable in levels for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in the 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: Heterogeneity by demographics in the impact of treatment on work status

($>$ 1 year after intervention)

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

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

Table A.12: 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.13: Robustness (Multiple Hypothesis Testing): Impact of treatment on employment outcomes (> 1 year after intervention)

	Work Status		Workdays (per month)		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)	-0.044	-0.018	-1.228	1.539	-0.367	0.221	-0.605	0.668
	(0.104)	(0.38)	(0.04)	(0.063)	(0.04)	(0.523)	(0.062)	(0.152)
	[0.191]	[0.195]	[0.191]	[0.084]	[0.191]	[0.244]	[0.191]	[0.115]
T1 (without network)	0.019	0.044	0.286	1.901	-0.009	0.661	0.196	1.195
	(0.527)	(0.029)	(0.656)	(0.024)	(0.959)	(0.064)	(0.574)	(0.012)
	[0.6]	[0.084]	[0.6]	[0.084]	[0.922]	[0.084]	[0.6]	[0.084]
Observations	1,377	1,377	1,377	1,377	1,377	1,362	1,377	1,377
R-squared	0.181	0.053	0.177	0.048	0.196	0.061	0.183	0.047
Mean Y	0.23	0.96	5.15	22.8	1.12	8.35	913.73	11199.24

Note: The dependent variable in columns (1)-(2) is an indicator variable that takes a value of one if an individual is working in the reference period and zero otherwise. In columns (3)-(4) and (5)-(6) the dependent variable is the number of days worked in a month and the number of hours worked in a day, respectively. In columns (7)-(8) the outcome is the log transformation of the monthly earnings in the reference period.'Mean Y' denotes the mean value of the corresponding dependent variable in levels for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in the current location) and individual characteristics (above primary education, age (in years), occupation type, mobile usage) at baseline. Original p-values from Tables 5,6 and 8 are reported in parentheses while p-values of Anderson's sharpened False Discovery Rate (FDR) q-values which adjust for multiple hypothesis testing are reported in square brackets.

Table A.14: Robustness (Multiple Hypothesis Testing): Impact of treatment on type of employment (> 1 year after intervention)

	Self-employed		Salaried		Wage labor	
	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)
T1 (without network)	-0.013	0.042	0.001	0.016	-0.034	-0.067
	(0.345)	(0.118)	(0.944)	(0.574)	(0.097)	(0.064)
	[0.425]	[0.548]	[0.894]	[0.755]	[0.348]	[0.548]
T2 (with network)	0.045	0.030	-0.002	0.039	-0.025	-0.016
	(0.043)	(0.349)	(0.855)	(0.215)	(0.149)	(0.69)
	[0.348]	[0.548]	[0.894]	[0.548]	[0.348]	[0.755]
Observations	1,377	1,377	1,377	1,377	1,377	1,377
R-squared	0.082	0.226	0.182	0.149	0.128	0.118
Mean Y	0.12	0.32	0.05	0.39	0.06	0.23

Note: The dependent variable is an indicator variable for type of work. In Columns(1)-(2), it takes value one if an individual is self-employed and zero otherwise. Similarly, Columns (3)-(4) and Columns(5)-(6) are indicator variables for salaried and casual labor, respectively. '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. Original p-values from Table 7 are reported in parentheses while p-values of Anderson's sharpened False Discovery Rate (FDR) q-values which adjust for multiple hypothesis testing are reported in square brackets.

Table A.15: Impact of treatment on labor market outcomes (ToT Specification) (> 1 year after intervention)

	Work Status		Workdays (per month)		Work hours (per day)		Earnings (per month)	
	Wife	Husband	Wife	Husband	Wife	Husband	Wife	Husband
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.055	0.042	-2.040	6.087**	-0.806	1.536	-0.889	3.267**
	(0.104)	(0.063)	(2.279)	(2.712)	(0.654)	(1.134)	(1.247)	(1.546)
Observations	1,377	1,377	1,377	1,377	1,377	1,362	1,377	1,377
R-squared	0.172	0.041	0.164		0.175	0.034	0.171	
Mean Y	0.23	0.94	5	22.75	1.05	8.15	-2.05	7.79

Note: 'Treatment' is a dummy variable that equals one if the respondent registered on the platform and zero otherwise. We use 2SLS estimation model and instrument the registration with a dummy for whether the respondent was offered platform registration i.e., if he/she was randomly assigned to either of the treatment arms - T1 or T2. The dependent variable in columns (1)-(2) is an indicator variable that takes a value of one if an individual is working in the reference period and zero otherwise. In columns (3)-(4) and (5)-(6) the dependent variable is the number of days worked in a month and the number of hours worked in a day, respectively. In columns (7)-(8) the outcome is the log transformation of the monthly earnings in the reference period. The p-values correspond to the test of equivalence in the treatment effect between the two treatment arms (T1 and T2). 'Mean Y' denotes the mean value of the corresponding dependent variable in levels for the control group at baseline. All specifications control for household characteristics (asset index, joint family, number of children, SC/ST, Hindu religion, native, and years staying in the 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.16: Robustness (Balanced Sample): Impact of treatment on employment outcomes (> 1 year after intervention)

	Work status		Workdays (per month)		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	-1.220**	1.490*	-0.356**	0.178	-0.590*	0.617
	(0.027)	(0.021)	(0.590)	(0.823)	(0.176)	(0.348)	(0.322)	(0.468)
T2 (with network)	0.018	0.044**	0.263	1.911**	-0.014	0.667*	0.186	1.199**
	(0.029)	(0.020)	(0.639)	(0.829)	(0.181)	(0.353)	(0.349)	(0.467)
Baseline Y	0.921***	0.149	0.188***	0.075	0.286***	0.184***	0.242***	0.086*
	(0.041)	(0.204)	(0.068)	(0.048)	(0.072)	(0.035)	(0.084)	(0.045)
p-value [T1=T2]	[0.03]	[0]	[0.01]	[0.48]	[0.06]	[0.06]	[0.02]	[0.06]
Observations	1,364	1,364	1,364	1,364	1,364	1,349	1,364	1,364
R-squared	0.188	0.054	0.185	0.050	0.203	0.061	0.190	0.048
Mean Y	.23	.94	4.94	22.7	1.03	8.13	879.67	11539.27

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

Table A.17: Robustness: Internal Validity

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

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

Table A.18: 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.19: Heterogeneity in self-employment status of wives by self-employment of her peers

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

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

Table A.20: Impact of treatment on employment outcomes of wife's network (2SLS) (> 1 year after intervention)

	Extensive Margin	Intensive Margin		
	Working	Days (Monthly)	Hours (per day)	Income (Monthly)
	(1)	(2)	(3)	(4)
	Panel A: Male peers			
Treatment	0.118***	3.685***	1.260***	2.176***
	(0.044)	(1.196)	(0.463)	(0.694)
Observations	394	394	389	394
R-squared	0.160	0.134	0.108	0.130
Mean Y	0.76	17.04	6.26	8217.27
	Panel B: Female peers			
Treatment	-0.025	-0.796	-0.311	-0.284
	(0.030)	(0.694)	(0.207)	(0.372)
Observations	1,428	1,428	1,427	1,428
R-squared	0.139	0.148	0.151	0.146
Mean Y	0.19	4.09	1.22	2197.06

Note: The sample consists of all (baseline + intervention) peers of the wife in T1, T2 and the control group. 'Treatment' is a dummy variable that equals one if the wife's peer was offered platform registration and zero otherwise. We use 2SLS estimation model and instrument the peers' treatment status with a dummy for whether the wife was randomly assigned to T2 or not. The dependent variable in column (1) is an indicator variable that equals one if the peer is working in the reference period, and 0 otherwise. Columns (2)-(4) are the number of workdays (per month), hours (per day), and log transformation of monthly earnings. ANOVA specification is used in this analysis as intensive margin data of peers is not reported at the baseline. 'Mean Y' denotes the mean value for the peers of wives in the benchmark group (control + T1) at Endline 1 of the dependent variable in Columns (1)-(3) and the mean value without log transformation for the dependent variables in Column (4). Standard errors clustered at PS level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table A.21: Impact of network treatment on interest in and registration on platform

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

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

Table A.22: Impact of network treatment on job-offers from platform (self-reported)

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

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

Table A.23: Impact of treatment on own attitude towards gender roles (> 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

Note: The dependent variables are the standardised Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the responses to questions on gender attitudes (Attitude1: It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family; Attitude2: It is more important for a wife to help her husband's career than to have one herself; Attitude3: When a mother works for pay, the children suffer, Attitude4: A working mother cannot establish just as warm and secure a relationship with her children as a mother who does not work). A higher value represents gender progressive attitudes. Columns (1)-(4), (5)-(8), (9)-(12) and (13)-(16) report the coefficients for first, second, third and fourth attitude, respectively. Columns (1)-(2) report the combined treatment effect using equation (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.24: Impact of treatment on own attitude towards women's outside work (> 1 year after intervention)

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

Note: The dependent variables are the standardised Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the responses to questions on gender attitudes. (Attitude1: In your opinion, is it acceptable for an adult woman to travel outside the locality if she wants to?; Attitude2: In your opinion, should an adult woman work outside of home if she wants to?; Attitude3: Do you approve of a married woman earning money if she has a husband capable of supporting her?; Attitude4: In your opinion, if the wife is working outside the home, should the husband help her with household/care duties?). A higher value represents gender progressive Attitudes. Columns (1)-(4), (5)-(8), (9)-(12) and (13)-(16) report the coefficients for first, second, third and fourth Attitude, respectively. Columns (1)-(2) report the combined treatment effect using equation (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).

C Further Alternative Explanations

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

Second, is it possible that network-mediated self-employment opportunities, e.g. changes in labor demand that wives in the network treatment group took advantage of through their network, could be driving their estimated self employment 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 do not find any differential treatment effects, suggesting that network-mediated access to demand for women's labor does not drive the results.

Third, could social comparison or competition among socially connected households, induced by the network treatment, be driving the positive employment effects that we observe among husbands in the network treatment group? We check that wives refer approximately 20% male peers (vast majority being family members and neighbors), among whom average employment rates are between 0.6-0.8, well below that of their husbands at baseline (0.96). Hence it appears that wives strategically pick male peers who are less likely to be competition for their husbands, suggesting that our explanation of greater job information sharing among peers in the network treatment group possibly remains the most plausible.