Gender heterogeneity in peer effects on work: Evidence from multidimensional social networks in rural India*

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Abstract

We investigate heterogeneous peer effects on male and female employment outcomes through various social networks in developing areas. Using data on social networks in rural India, we find a strong peer influence on female labor supply, regardless of peer types, such as friends, relatives, and risk-sharing partners, whereas men's work decisions seem to be unaffected. The peer effects on female labor supply are mostly driven by peers' aggregate outcome rather than the average outcome of peers. The results indicate the presence of social multiplier effects such that having more women who work in rural villages amplifies women's labor force participation. The same-gender network neighbors have a stronger impact on the female labor supply than the opposite-gender peers. Moreover, we find that women respond to peers' aggregate decisions on working outside their village, whereas men's work locations are more subject to peers' average outcome. Our findings imply that policymakers could utilize social network information to improve women's employment and welfare.

JEL: J16, J21, O10, C31

Keywords: Gender heterogeneity; peer effects; employment outcomes; multidimensional social networks; social norm; social multiplier

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1 Introduction

Understanding how various social relations affect labor market outcomes is essential because social networks play a central role in transmitting information on job openings and worker productivity (Granovetter, 1973; Calvo-Armengol and Jackson, 2004; Jackson, 2011). Social networks are vital for job search, particularly in developing countries, because employment opportunities are widely driven by informal institutions (Assaad, 1993). Interestingly, men and women tend to have different social relationships (Benenson, 1990), and cultural traditions and social norms determine gender roles in the labor market (Fernandez, 2007; Alesina et al., 2013; Jayachandran, 2015). Accordingly, the impact of such social relationships on economic behavior may vary by gender. In this paper, we examine how peers affect male and female labor market outcomes through various social relations in developing areas.

Specifically, we investigate the peer influence through multidimensional social networks (friendship, relatives, and risk sharing) on work decisions of men and women in rural India. Over the last century, female labor force participation (LFP) has increased sharply in most developed countries (Eckstein and Lifshitz, 2011; Fogli and Veldkamp, 2011), but this pattern is not observed in India. Figure 1 shows the LFP rate in India over time. Male LFP remains relatively high and steady, whereas female LFP stays at a low level, with a slightly declining trend in rural areas. Thus, understanding how peers influence labor supply would have important policy implications, particularly among women.

[Figure 1]

We use a linear-in-means model to identify peer effects. A well-known challenge in identifying peer effects is the reflection problem (Manski, 1993). An individual influences his or her friends' outcomes and vice versa. Additionally, individuals in a group share similar observed and unobserved characteristics or institutional backgrounds, leading to an endogeneity problem. Bramoullé et al. (2009) and Liu and Lee (2010) show that researchers can identify endogenous peer effects using an instrumental variable (IV) approach when individuals' reference groups do not fully overlap. In line with their econometric findings, we tackle the endogeneity problem by using indirect friends' characteristics as IVs. We further include village fixed effects and run a few falsification tests to control for unobserved factors that may correlate with peers' labor market outcomes.

We distinguish two mechanisms by which peers may influence labor market outcomes: the social norm effect and social multiplier effect (Liu et al., 2014). The social norm effect indicates that an individual mimics peers' behavior, and thus, the peers' average outcome (i.e., the proportion of peers who work) influences the individual's own work decision. By contrast, the social multiplier effect states that finding an available job would be easier as the number of peers who work increases. These two mechanisms must be considered together as peer effects on employment may go through different channels by gender, such as peer pressure, the quality of job matching or job information.

We find gender heterogeneity in peer effects on labor market outcomes, using the "Social Network and Microfinance" dataset, collected by Banerjee et al. (2013). In general, men's work decisions (whether to work or not) are not influenced by their peers, regardless of peer types, indicating relatively inelastic labor supply among men with respect to peers' outcomes. Meanwhile, women's work decisions are affected by peers' aggregate outcomes through all types of peer relations, implying the social multiplier effect. If a woman has one extra peer who works, her work probability increases by approximately ten percentage points. The positive peer effect among women is mostly driven by female peers rather than male peers. Our findings suggest that having more working female network neighbors facilitates women's job matching and allows women to share more job information. Additionally, friends and risk-sharing peers equally influence women's decision to work outside the village through the social multiplier effect rather than the social norm effect.

Our study contributes to the literature that explores the importance of social connections in labor market outcomes in several ways. First, we investigate gender heterogeneity in peer effects through various types of relations, that is, friends, relatives, and risk-sharing partners. A few recent papers examine the peer influence on female LFP, using social networks or family data in the United States or Europe (Maurin and Moschion, 2009; Mota et al., 2016; Nicoletti et al., 2018). Moreover, several other studies distinguish more helpful types of social ties when obtaining a job. Granovetter (1973), Gee et al. (2017), Kramarz and Skans (2014), and Patacchini et al. (2017) find that various types of peers in terms of the relationship strength have different effects on educational attainment and employment. Social connections are multidimensional, and we investigate whether different peers – friends, relatives, and risk-sharing partners – consistently influence male and female employment decisions.

Second, this is the first study that distinguishes the social norm and social multiplier effects in the context of labor supply decisions. Liu et al. (2014) study peer effects in education and sports activities and find that students tend to exhibit the social norm effect by conforming to their friends' average study effort while showing both social multiplier and social norm effects for the involvement in sports activities. Social incentives or the presence of peers are also found to play a role in workers' productivity. For instance, Bandiera et al. (2010) find that workers' productivity is higher (lower) when they work with more-able (less-able) friends, which is consistent with the social norm behavior. Songsermsawas et al. (2016) find positive peer effects on agricultural revenues in India. To the best of our knowledge, no prior study investigates the relative importance of social norm and social multiplier effects in a unified framework, although a few studies have documented the social norm or social multiplier effect individually in the context of labor supply (e.g., Mota et al., 2016),

Lastly, this paper concerns the unique environment of rural India, whereas most of the previous works on peer effects in the labor market focus on developed countries, Social networks' role in employment and policy implications of peer effects are different between developed and developing countries. In developing countries, the standard job search may rely on informal networks, where individuals obtain help from their peers to search for jobs. This informal job search could even be more prevalent in rural areas because of limited employment opportunities, lack of transparent information on job availability, and lack of a formal job search process. In this context, our study provides evidence of peer effects as decisive determinants of female labor supply.

2 Conceptual framework and relevant literature

Peers or social networks are important determinants of individual behavior (e.g., Epple and Romano, 2011; Hahn et al., 2020) and affect various labor market outcomes (Calvo-Armengol and Jackson, 2004). Peers may influence an individual's labor market outcomes through several channels. First, individuals may wish to conform to their peers or mimic their peers' behavior in the labor market. This mechanism is called the social norm or local average effect. In the local average effect model, individuals' utility decreases as they deviate from their average peers' behavior. This model predicts that individuals want to conform as much as possible to their peers' social norm, which is defined by their peers' average behavior.

The second channel is a social multiplier or local aggregate effect, such that the sum of peers' efforts or behavior magnifies one's outcome. For instance, an individual will enjoy the higher marginal utility of exerting effort in finding a job when his or her reference group has more employed people (Liu et al., 2014). Similarly, one may exert effort to find a job, and the return to this effort can be higher when more employed peers are around as they are likely to provide information on job opportunities. The social multiplier effect is consistent with strategic complementarity in that individuals' efforts reinforce each other. The social multiplier framework is suitable for studying the extensive margin of labor supply as well as individuals' work location. For instance, our data allow us to test whether peers influence the decision to work outside the village. The more people who work outside the village in one's reference group, the more he or she could obtain information on opportunities to work there.

A few previous studies document the importance of peers in employment and contribute to our understanding of how policymakers use peer effects or social ties to enhance overall labor supply. For instance, Cingano and Rosolia (2012) verify that the unemployed duration of Italian workers exogenously displaced by firm closures is affected by various features of the former co-workers, including their employment status. Using British data, Cappellari and Tatsiramos (2015) confirm that the better network quality, measured by the number of employed friends, enhances the job-finding rate, which is consistent with the idea of social multiplier effects.

Existing literature has also studied the association between the size of peer effects and the intensity of social relations. Kramarz and Skans (2014) find that strong social ties (of parents) are critical determinants for young adults' first job, and workers with strong social ties are more likely to remain in the first entry job in Sweden. Using six million American Facebook users' data, Gee et al. (2017) find that a single stronger tie provides more significant help in finding a job than a weak tie. This finding is contrary to Granovetter's (1973) result that weak ties are more valuable than strong ties for job opportunities. There is sparse yet emerging evidence that peers influence individuals' job choices. Schmutte (2014) finds that workers who have neighbors with high-paying jobs tend to change jobs and are more likely to move to higher-paying firms. Using the panel data of a German local labor market, Cornelissen et al. (2017) show that peer effects vary across types of occupations.

Our analysis of gender-specific peer effects relates to the strand of literature that focuses on gender heterogeneity or inequality in labor market outcomes. According to the Global Gender Gap Report 2017 (World Economic Forum, 2017), the gap between women and men in economic participation is 58%, indicating that women's LFP rate is barely more than half that of men. Among many possible reasons behind the gender gap, Fernández (2013) documents a strong positive association between female LFP rate and social attitude. Jayachandran (2015) suggests that cultural features deteriorate gender inequality in less developed countries. There is also a study that economic growth hinders women's LFP. Mehrotra and Parida (2017) find that India's female LFP rate is declining because women have limited opportunities because of their low education and growing mechanization.

In this context, it is meaningful to investigate the potential role of social networks in improving female LFP and the gender gap in employment in developing areas. Using the French Labor Force survey, Maurin and Moschion (2009) find a social multiplier effect on LFP of mothers living in the same neighborhood. Mota et al. (2016) show that American women mimic the work decisions of nearby peers. Nicoletti et al. (2018) find that family peers influence mothers' working hours in Norway. Those papers focus on developed countries, but studies on social networks and LFP in developing areas are rare.[1]

[1]Beaman et al. (2018) suggest the importance of social networks in female LFP by showing that referral-based hiring is a potential channel behind gender inequality in Malawi's labor market.

3 Data

We use the publicly available version of the "Social Networks and Microfinance" dataset, collected by Banerjee et al. (2013) from 75 villages in rural Karnataka, a state in the southwestern region of India. It is a cross-sectional dataset, surveyed by Banerjee et al. (2013) in 2006. The dataset includes a full census of households and a detailed survey for the sub-sample (46%) of individuals. The average population per village is approximately 900, and over half of the households were surveyed (Jackson et al., 2012). The eligible members and their spouses in each household are also surveyed to answer their socioeconomic background information.

3.1 Individual-level data

The raw data comprises 16,984 individuals. We restrict our final sample to individuals aged 18–65 because our analysis focuses on village individuals' work decisions. We delete observations with missing values for some survey questions, leading to a drop of less than 0.5% of the original sample. Hence, the final sample comprises 16,484 adults across 75 villages. Table 1 reports the descriptive statistics of the data. Individual-level variables are age, years of education, a dummy variable reflecting for the Hindu religion, and dummy variables for general caste, village native, and speaking the Kannada language, a major language in Karnataka. The mean age is around 39 years, and the average number of years of education is five. The proportion of general-caste individuals is 12%, and the rest are in one of the following three categories: Scheduled Caste, Scheduled Tribe, and Other Backward Class. The majority (90%) of men are village natives, whereas only 28% of women are village natives. This statistic is consistent with Fulford's (2015) estimates, who find that two-thirds of all Indian women migrated for marriage. More than 95% of village individuals identify themselves as Hindus, and 22% speak Kannada.

[Table 1]

We focus on two labor market outcome variables under empirical strategy: work and work outside the village. The variable "work" takes a value of one if an individual has worked during the last week and zero otherwise. Note that this variable is different from labor market participation because we do not observe whether people did not work during the last week but actively seeking employment opportunities. Hence, the variable represents one's employment status against non-employment. This employment outcome includes not only having paid work but also self-employment and work for a family business. Using this variable as an outcome variable, we investigate how an individual's decision to work is affected by peers' average or aggregate work status. For example, if a woman is more likely to work when she has a paid working female friend, then it may indicate a positive peer effect through a friendship network.

The second labor market outcome variable is concerned about work location. We construct a binary variable, "work outside," which takes a value of one if an individual's workplace is outside his/her village. In rural areas with a limited diversity of occupations, the decision to work outside the village may require job introduction by an acquaintance. Besides, in rural areas, women's decisions to work outside their village may be strongly discouraged because they may need to concentrate on household labor, such as child-rearing and food preparation, and be asked to help other women.

As Table 1 shows, 63% of the survey respondents had worked for a week before the survey was fulfilled. This number varies substantially by gender: 87.7% of men worked, whereas only 43.1% of women did. Additionally, 35% of men worked outside the village, whereas only 10% of women did so.

3.2 Network data

The dataset also includes household- and individual-level network information, and we focus on three major social relations among village individuals.[2] First, we use the close non-relative network as a friendship network, and second, we use the close relative network as a relative network. Third, we combine the two network relations, namely "borrow money from" and "lend money to," to construct the informal borrowing network related to money, which we call the risk sharing network. By combining, we mean that i and j have a link in the resulting network if they form a link in one or both of the original networks (either borrowing or lending or both).

Table 2 shows the number of network connections or degrees by peer type and gender.[3] The first three columns show the average number of network connections for all individuals and the proportion of men and women among those network connections. Specifically, village individuals have about eight friends, seven close relatives, eight informal risk-sharing partners.[4] They have more male relatives (51.7%) but more female friends (54.8%) and risk-sharing partners (53.9%). The next six columns show that men have slightly more network connections than women. Women tend to have more same-gender friends and risk-sharing partners than men do. Both men and women have more relatives of different genders.

[Table 2]

[2]There are a total of 14 social networks in the data: (1) close relatives; (2) close non-relatives; (3) borrow money from; (4) lend money to; (5) borrow kerosene or rice from; (6) lend kerosene or rice to; (7) visit other's home; (8) others visit your home; (9) give advice; (10) ask for advice; (11) temple-company; (12) medical-help; and additional two networks, namely (13) the intersection of all relationships and (14) the union of all relationships.

[3]The degree of a node in a network is the number of links that the node has. Thus, in this friendship network context, a node is an individual, and the degree of the node is the number of the individuals' friends.

[4]Although the survey limits the number of network neighbors each individual can nominate, the cap does not bind for most individuals (Jackson et al., 2012).

3.3 Peer's labor outcomes and characteristics

Using the labor outcome variables of village individuals and their network relations, we construct peers' labor outcomes (work decision and work location). This subsection describes the summary statistics of such peers' labor outcomes and how they are (unconditionally) correlated with the original outcome variables. We focus on different types of peers (friends, relatives, and risk-sharing partners). Those peers may partly overlap with each other. Furthermore, we divide peers by their gender, and thus, we obtain male and female network neighbors. Hence, we have outcomes for six different types of peers: male friends, female friends, male relatives, female relatives, male RS partners, and female RS partners.

We also construct both the average and aggregate peer outcomes for each peer type and each outcome. Specifically, for each individual's outcome variable, we calculate the average value of his or her peers' outcome and the sum of those peers' outcome. As we will explain in our empirical strategy, the former, or the average peer outcome, captures how individuals are willing to conform to the social norm. The latter, or the aggregate peer outcome, captures the social multiplier effect. Note that peer outcomes with different peer types are correlated with each other. For example, friends' work decisions are correlated with relatives' work decisions. Therefore, we include each type of peer outcome one at a time to capture the peer effect through each type of relationship more precisely, .

Table 3 shows the summary statistics of peers' outcomes. On average, 68% of men's friends and 60% of women's friends worked during the last week of the survey. Men have more RS partners who worked than women do. By contrast, 59% of men's relatives worked, whereas 72% of women's relatives worked. This gap is partly because village men and women have more relatives of different genders, so women's relatives are more likely men and vice versa. Regardless of peer types, the aggregate number of working peers working is greater for men than for women. This pattern is similarly displayed for the other outcome variable, working outside the village.

[Table 3]

4 Empirical strategy

4.1 Empirical model

We have a set of individuals $N = \{1, \cdots, n\}$, partitioned into R villages. There are n_r individuals in the rth village, and we observe social networks of type s, s ={FR, REL, RS} among them, where FR, REL, and RS refer to friends, relatives, and risk-sharing partners, respectively. We employ an adjacency matrix $G^s_r = [g^s_{ij,r}]$ to denote network s in village r, where $g^s_{ij,r} = 1$ if i and j are connected with relation s, and $g^s_{ij,r} = 0$, otherwise. For example, if i and j in village r are friends, then $g^{\mathrm{FR}}_{ij,r} = 1$. We also set $g^s_{ii,r} = 0$ for all i. The reference group of individual i in network s is the set of i's network neighbors and denoted by $N^s_{i,r} = \{j \neq i | g^s_{ij,r} = 1\}$. The size of the reference group of i is $g^s_{i,r} = \sum_{j=1}^{n_r} g^s_{ij,r}$, which is also called the degree of i (in the network of type s).

Let $W^s_r = [w^s_{ij,r}]$, where $w^s_{ij,r} = g^s_{ij,r}/g^s_{i,r}$ be the row-normalized adjacency matrix. Each element of this matrix captures the relative importance of each link to individuals. For example, consider a friendship pair i and j, that is, $g^{\mathrm{FR}}_{ij,r} = 1$. If i has three friends and j has two friends, then $w^{\mathrm{FR}}_{ij,r} = 1/3$ and $w^{\mathrm{FR}}_{ji,r} = 1/2$ in the row-normalized adjacency matrix. Hence, j is one of i's three friends, whereas i is one of j's two friends. If a researcher believes that the effect of i's actions on j may be stronger than the effect of j's actions on i, then adopting the row-normalized network W^s rather than G^s may be more reasonable.

We consider the following three different models of peer effects:

- the local average (LAVG) model;
- the local aggregate (LAGG) model; and
- the unified model that incorporates both LAVG and LAGG peer effects.

The LAVG peer effects model through network s can be written as follows.[5]

$$y_{i,r} = \alpha + \beta_1 \sum_{j=1}^{n_r} w^s_{ij,r} y_{j,r} + x'_{i,r}\delta + \sum_{j=1}^{n_r} w^s_{ij,r} x'_{j,r}\gamma_1 + \xi_r + \varepsilon_{i,r}, \tag{4.1}$$

where $y_{i,r}$ is i's labor market outcome of interest, such as an indicator of working or an indicator of working outside village r. The variable $x_{i,r}$ is a vector of characteristics of i that accounts for observed differences of individual i, such as age and educational attainment. The parameter β_1 captures the LAVG peer effect since $\sum_{j=1}^{n_r} w^s_{ij,r} y_{j,r}$ is the average outcome of i's peers (of type s) in village r. The model also includes the average characteristics of peers $\sum_{j=1}^{n_r} w^s_{ij,r} x_{j,r}$ and village fixed effects ξ_r. The LAVG effect represents the role of social norms, for example, conformist behavior or peer pressure (Patacchini and Zenou, 2012; Liu et al., 2014; Blume et al., 2015; Boucher, 2016).

Second, we consider the following LAGG model:

$$y_{i,r} = \alpha + \beta_2 \sum_{j=1}^{n_r} g^s_{ij,r} y_{j,r} + x'_{i,r}\delta + \sum_{j=1}^{n_r} g^s_{ij,r} x'_{j,r}\gamma_2 + \xi_r + \varepsilon_{i,r}. \tag{4.2}$$

The fundamental distinction between the LAGG model and the LAVG model is that the LAGG model replaces the (i, j) element of the row-normalized adjacency matrix with that of the non-row-normalized. Hence, the model includes the aggregate outcome of i's

[5]The LAVG model is also known as the linear-in-means model (Manski, 1993).

peers (of type s) in village r, $\sum_{j=1}^{n_r} g_{ij,r}^s y_{j,r}$. For example, if y_i is the "work" variable, then $\sum_{j=1}^{n_r} g_{ij,r}^{\mathrm{FR}} y_{j,r}$ indicates how many friends of i worked last week. Consequently, the parameter β_2 captures the LAGG peer effect, implying "having more working friends, more likely to influence an individual to work." The LAGG effect represents strategic complementarities among individuals (Bramoullé and Kranton, 2007; Ballester et al., 2010).

Lastly, we employ a unified model that includes both the LAVG and LAGG peer effects through network s:

$$\begin{aligned} y_{i,r} = \alpha + \beta_1 \sum_{j=1}^{n_r} w_{ij,r}^s y_{j,r} + \beta_2 \sum_{j=1}^{n_r} g_{ij,r}^s y_{j,r} + x_{i,r}'\delta \\ + \sum_{j=1}^{n_r} w_{ij,r}^s x_{j,r}'\gamma_1 + \sum_{j=1}^{n_r} g_{ij,r}^s x_{j,r}'\gamma_2 + \xi_r + \varepsilon_{i,r}. \end{aligned} \tag{4.3}$$

Having two different peer effects in one model allows us to account for two types of equilibrium behaviors, taste for conformity and strategic complementarities while controlling for each other.

Let $\mathbf{Y}_r = \{y_{1,r}, \ldots, y_{n_r,r}\}'$ and $\mathbf{X}_r = \{x_{1,r}, \ldots, x_{n_r,r}\}'$, and $\epsilon_r = \{\varepsilon_{1,r}, \ldots, \varepsilon_{n_r,r}\}'$. Denote the n_r-dimensional vector of ones by $\mathbf{1_{n_r}}$. Then, three models (4.1)–(4.3) can be written in matrix form as

$$\text{LAVG: } \mathbf{Y}_r = \alpha + \beta_1 W_r^s \mathbf{Y}_r + \mathbf{X}_r'\delta + W_r^s \mathbf{X}_r'\gamma_1 + \xi_r \mathbf{1}_{n_r} + \epsilon_r, \tag{4.4}$$

$$\text{LAGG: } \mathbf{Y}_r = \alpha + \beta_2 G_r^s \mathbf{Y}_r + \mathbf{X}_r'\delta + G_r^s \mathbf{X}_r'\gamma_2 + \xi_r \mathbf{1}_{n_r} + \epsilon_r, \tag{4.5}$$

$$\text{Unified: } \mathbf{Y}_r = \alpha + \beta_1 W_r^s \mathbf{Y}_r + \beta_2 G_r^s \mathbf{Y}_r + \mathbf{X}_r'\delta + W_r^s \mathbf{X}_r'\gamma_1 + G_r^s \mathbf{X}_r'\gamma_2 + \xi_r \mathbf{1}_{n_r} + \epsilon_r. \tag{4.6}$$

We stack the data over R villages to construct the models for the entire sample.

4.2 Identification

There are a few identification challenges in the peer effect models. The first challenge is the endogeneity of the peer's average or aggregate outcome. As we can see in equations (4.4)–(4.6), the vector of outcome variable $\mathbf{Y}_r$ appears on the right-hand side, leading to a simultaneity problem. Intuitively, we have to infer whether the average or aggregate behavior in some group influences the individuals' behavior in the group. Suppose a person changes his or her behavior. In that case, it is difficult to distinguish whether the mirror image (the group behavior) causes the change in the person's behavior or the person's behavior changes the group behavior.

Second, as Manski (1993) points out, when the reference group does not vary across individuals, individuals' average or aggregate behavior within the group has perfect collinearity with their average or aggregate characteristics. In this case, we cannot disentangle the LAVG and/or LAGG effects from the exogenous effects of peer characteristics captured by γ. Additionally, individuals within the same village share the same environment and similar incentives or shocks, all of which could let village individuals behave similarly (Dharmalingam and Philip Morgan, 1996), leading to correlated effects (Manski, 1993).[6]

In the social network setting, the reference group varies across individuals. Thus, using the variation in the average or aggregate peer behavior across individuals, we can identify the peer effects. To be specific, Bramoullé et al. (2009) show that if matrices in $\{I, W_r^s\mathbf{X}_r, (W_r^s)^2\mathbf{X}_r, (W_r^s)_r^3\mathbf{X}_r\}$ or in $\{I, G_r^s\mathbf{X}_r, (G_r^s)^2\mathbf{X}_r, (G_r^s)^3\mathbf{X}_r\}$ are linearly independent, the peer effects are identified by an IV approach. Finally, we control for correlated effects by including village fixed effects ξ_r.

Adopting the IV approach of Bramoullé et al. (2009), we use $\{(W_r^s)^2\mathbf{X}_r, (W_r^s)^3\mathbf{X}_r\}$ and $\{(G_r^s)^2\mathbf{X}_r, (G_r^s)^3\mathbf{X}_r\}$ as sets of excluded IVs for the LAVG and LAGG variables, respectively, to run two-stage least squares (2SLS) estimation. Intuitively, these instruments contain empirical information about the average or aggregate characteristics of indirect friends of the second and third degrees. Thus, the identification of the peer effect parameters hinges on the assumption that indirect peers' average or aggregate characteristics are not associated with i's unobserved attributes after controlling for individual i's own characteristics, the observed attributes of i's direct network neighbors, and village fixed effects.

We assume that indirect peers' characteristics are uncorrelated with the unobserved attribute of i after controlling for the characteristics of i's direct network neighbors. Nevertheless, one may have concerns about measurement errors in the nomination of network connections or individuals' sorting into a particular village. For example, some of the direct network neighbors may not be nominated as direct connections by mistake during the survey. Additionally, people with similar labor tendencies or skills may have gathered in the same village because of the village's working conditions. To address these concerns related to the correlated effects, we run falsification tests by creating fictitious network neighbors within each village and within the same caste. The tests confirm that our results on peer effects are not a consequence of sorting or measurement errors, obtained by a random chance. We will explain further details about the falsification tests in Section 6.

4.3 Estimation of the gender gap in peer effects

To empirically analyze the gender gap in peer effects, we apply the following two approaches. First, we split the sample into men and women and investigate how peer

[6]Correlated effects refer to the tendency that individuals in the same reference group behave similarly because they have a common shock or environment.

effects differ by respondents' gender. This practice is essential to reveal heterogeneous peer effects on labor outcomes between men and women, regardless of peers' gender, because the social norm and multiplier effects may vary by gender.

Second, we examine another dimension of the gender gap in peer effects: heterogeneity in male peers' effects and female peers' effects. We decompose one's network neighbors (of type s) into male and female peers for this analysis. Specifically, let $G_r^{\mathrm{M},s}$ be the adjacency matrix representing the network of male neighbors, such that $g_{ij,r}^{\mathrm{M},s} = 1$ if i and j are connected and j is a male and zero otherwise. We similarly define the female network $G_r^{\mathrm{F},s}$ if i and j are connected and j is a female, and zero otherwise. The row-normalized version of the male and female networks is $W_r^{\mathrm{M},s}$ and $W_r^{\mathrm{F},s}$, respectively. Then, we extend the unified model as follows:

$$\begin{aligned}\mathbf{Y}_r = \alpha &+ \beta_{\mathrm{M1}} W_r^{\mathrm{M},s}\mathbf{Y}_r + \beta_{\mathrm{M2}} G_r^{\mathrm{M},s}\mathbf{Y}_r + \beta_{\mathrm{F1}} W_r^{\mathrm{F},s}\mathbf{Y}_r + \beta_{\mathrm{F2}} G_r^{\mathrm{F},s}\mathbf{Y}_r \\ &+ \mathbf{X}_r'\delta + W_r^s\mathbf{X}_r'\gamma_1 + G_r^s\mathbf{X}_r'\gamma_2 + \xi_r\mathbf{1}_{n_r} + \epsilon_r.\end{aligned} \tag{4.7}$$

The parameters β_{M1} and β_{M2} (β_{F1} and β_{F2}) reveal the LAVG and LAGG peer effects from male (female) network neighbors, respectively. As explained in the previous subsection, we construct similar IVs that exploit the characteristics of indirect peers of the second and third degrees, using the four gender-specific networks: $G_r^{\mathrm{M},s}$, $G_r^{\mathrm{F},s}$, $W_r^{\mathrm{M},s}$, and $W_r^{\mathrm{F},s}$.

5 Results

5.1 Employment outcomes

The first outcome of interest is whether an individual is employed or not, which takes a value of one if an individual has worked during the last week and zero otherwise. In Tables 4 and 5, we report the baseline results of the LAVG and LAGG effects on individuals' work decisions, based on equations (4.4) and (4.5), respectively. The LAVG measures the effect of an increase in peers' average work probability (the social norm effect). The LAGG measures the effect of having an extra working peer (the social multiplier effect). The two effects, however, can be positively correlated in some cases.[7] To separately identify the LAVG and LAGG effects, in Table 6, we show the results when we add both the LAVG and LAGG effects in one regression as in equation (4.6). All regressions control for individual characteristics, peers' characteristics, and village fixed effects. Standard errors are clustered at the village level.

[Table 4]

[Table 5]

[7] For instance, if an individual befriends a new working person, both the proportion of working friends (i.e., relevant to the LAVG) and the number of working friends (i.e., relevant to the LAGG) increase.

The ordinary least squares (OLS) estimation results reported in panel A of Tables 4 and 5 show a strong positive association between an individual's labor outcome and peers' outcome for all peer types, for both men and women. Given that the OLS estimate of the peer effect can be biased, we focus on the IV results. Panel B of Tables 4 and 5 reports the 2SLS results of peer effects along with the coefficients of individual characteristics that could determine the employment outcomes, which we briefly discuss here.

The results on own characteristics suggest that the work probability increases with individuals' own age at a decreasing rate for both genders. Other than age, only education is a strong predictor of labor supply for men, which increases the probability of working at a diminishing rate. The result of the effect of women's education on work probability is consistent with findings in the previous research. The negative effect of education on women's labor supply may reflect a U-shaped pattern between education and female LFP, as shown by Fletcher et al. (2017) using the Indian National Sample Survey for 2011–2012.[8] We also find a negative effect of General Caste and a positive effect of having the Hindu religion on employment. The results are in line with the finding of Field et al. (2010) that Muslim women face the severest social restrictions on LFP, followed by the upper-caste Hindu women and the Scheduled Caste Hindu women. We note that the magnitudes and signs of coefficients on the own characteristics are similar when the peer outcomes change from the LAVG variable to the LAGG variable. Such an invariance implies that the correlation structure between peers' outcomes and individual characteristics does not differ systematically by how we construct the peer outcomes (LAVG or LAGG).

In terms of peer effects, the effects are absent for men in both Tables 4 and 5. For women, Table 4 shows positive social norm effects on the work decision when peers are defined by relatives, whereas Table 5 suggests a positive social multiplier effect with all definitions of peers. In Table 6, we include both LAVG and LAGG peer outcomes in one regression to show the effect of each channel while controlling for the other.[9] Therefore, the estimate of the LAVG effect shows the importance of the social norm channel while holding the social multiplier channel constant.

[Table 6]

[8]Fletcher et al. (2017) find that women receiving secondary schooling exhibit the lowest level of LFP in rural and urban areas. Given that the average years of education for women in our sample are 4.5 years, the effect of education on labor supply in our data is likely to operate at the declining region of the U-shape.

[9]The example of changing the LAVG variable while holding LAGG constant is as follows. If an individual has an extra non-working friend, the proportion of friends who work decreases without affecting the aggregate number of friends who work. Similarly, to consider the change in the LAGG variable while holding the LAVG constant, one may need to increase the number of working peers but fix the fraction of non-working ones. For instance, when the numbers of working and non-working friends are ten and five, respectively, having two extra working friends and one extra non-working friend would increase the aggregate number of working friends by two without altering the proportion of working friends.

The results in all three tables (Tables 4, 5, and 6) consistently confirm that peer effects are heterogeneous by gender. For men, peer effects are absent in both LAVG and LAGG models, indicating an inelastic labor supply decision among them. This could be due to a tradition or social norm suggesting that it is more efficient for men to work (Alesina et al., 2013). The results for women show that as a woman faces one extra peer who works, which is about a 0.6 standard-deviation increase in peers' aggregate work status (based on Table 3), her work probability increases by approximately ten percentage points. For this social multiplier channel, we do not see much difference in the magnitude of the effects across peer types, and the effects are significant for all peer types, i.e, friends, relatives, and risk-sharing partners.

Our results resonate the findings of Mota et al. (2016). They find no evidence of peer effects among men using the 1985, 1989, and 1993 waves of the American Housing Survey panel. For women, they find that having one more working peer to a woman's neighborhood increases the likelihood of working by 4.5 percentage points, and that peer effects in labor supply operate through women emulating the work behavior of other women who have children of similar age in their neighborhood. Our estimates seem larger, but the effect is not directly comparable. Institutional and contextual differences exist between the U.S. and rural India, as well as in peer definitions. Mota et al. (2016) define peers at a larger neighborhood level, whereas we define peers as an individual's close circle of friends or relatives.

The results so far suggest that women tend to be affected by their peers' aggregate behavior. We further examine whether this positive effect is driven by the same-gender or opposite-gender peers. Table 7 reports gender-specific peer effects, where we examine male and female peer effects separately. Consistent with our previous results, the social norm effect reported in panel A generally plays a little role in influencing women's work decision, although the effect of female friends is marginally significant at the 10% significance level. Given the standard deviation of the average fraction of female friends who work is 0.284 (Table 3), the result indicates that a one standard deviation increase in the fraction of female friends who work increases the work probability of women by roughly 3.8 percentage points (0.134*0.284).

[Table 7]

The results in panel B suggest that women's decisions to work are particularly influenced by the aggregate behaviors of same-sex friends, relatives, and risk-sharing partners rather than those of the opposite-sex. For instance, having one additional working female friend increases women's work probability by 14 percentage points, whereas having an extra working male friend has a negligible effect on women's employment outcomes. Similarly, having one additional female working relative or risk-sharing partner increases women's likelihood of working by 15.8 and 10.8 percentage points, respectively, whereas the addition of working men does not yield a measurable effect. The results are consistent when we combine the LAVG and LAGG effects, as reported in Appendix Table A1.

5.2 Working outside the village

The second labor market outcome variable is regarding work location. We construct a binary variable indicating whether an individual works outside the village. Given that most men work, peers might affect other aspects of labor market outcomes, such as work locations, in a more relevant margin. In our sample, roughly one-third of men work outside the village, whereas only 10% of women do so. Given the traditional expectation for women to focus on domestic work, working outside the village might be even more difficult for them than working within the village although jobs outside the village may offer a more lucrative wage. In fact, using the National Family Health Survey of married women ages 15–49 years, Heath and Tan (2020) show that few women can go to market alone (roughly 50%–60%) and even fewer women can leave the village alone (40%–45%). Our dataset allows exploring the importance of peer effects not only on the extensive margin of labor supply but also on the location of their job (within or outside the village).

Table 8 reports the peer effects on the decision to work outside the village in the model with both LAVG and LAGG effects. Men increase their likelihood of working outside the village as more fraction of friends work outside the village, indicating the presence of social norm effects. Compared with the effect on employment decisions, which was small and insignificant, the effect on working outside the village is sizable for men. A one standard deviation increase in the fraction of friends who work outside the village (0.255, Table 3) raises the likelihood of men working outside the village by 19 percentage points.

[Table 8]

For women, a one standard deviation increase in the number of friends working outside the village (0.939, Table 3) increases the probability of working outside the village by roughly 6.4 percentage points. This social multiplier effect is also present for risk-sharing partners. Additionally, we find that the overall pattern is similar when we restrict the sample of those who work, except that the magnitude of the LAGG effect on women's decisions becomes larger (Appendix Table A2). This positive LAGG effect for women indicates that in rural areas with a limited diversity of occupations, both the overall labor supply and the tendency to work outside the village are facilitated through job introduction by their network neighbors.

Overall, our results suggest that the social multiplier effect through social networks might be an important avenue for women to increase their labor supply. Our findings are in line with that of Cappellari and Tatsiramos (2015) who stress the importance of informal contacts as a source of information in job search using the British Household

Panel Survey. They show that a higher number of connections to employed people increase the job finding rate. Although we do not have information on wages, we find that a higher number of friends or risk-sharing peers encourage women to work outside the village, where jobs available outside the village may be higher-paying ones than those available within the village.

6 Falsification tests

To further validate our findings to the potential identification threat that the results may be driven by the correlation of labor outcomes across individuals within the same village and/or caste, we run two falsification tests. In the first test, we construct a fictitious network F_r^s that has the same number of connections as the true network G_r^s in each village, where all connections are randomly assigned within the village. We replace only i's direct network neighbors, that is, the first degree connections, with fictitious ones. We then estimate the model using $\{G_r^s F_r^s \mathbf{X}_r, (G_r^s)^2 F_r^s \mathbf{X}_r\}$ as excluded IVs for the fictitious peers' aggregate outcome $F_r^s Y_r$ after controlling for the aggregate characteristics of such peers, $F_r^s \mathbf{X}_r$. Using the row-normalized version of F_r^s, we define the fictitious peers' average outcome and corresponding IVs similarly. For the second-degree connections, we use the true nominated network, G_r^s. Hence, we can test whether randomly chosen residents (e.g., fictitious friends) in the same village affect an individual's labor outcomes.

Second, we construct another fictitious network F_r^s that has the same number of connections as the true network G_r^s in each village, where all the connections are randomly assigned among whom are those in the same caste of i within the same village. We select friends particularly from the same caste because the caste system has traditionally determined individuals' career choices (Munshi and Rosenzweig, 2006). We test whether randomly chosen residents of the same caste in the same village affects an individual's labor outcomes.

Tables 9 and 10 show the falsification results for the decision to work and work outside the village, respectively. The results confirm that our estimated peer effects, particularly, the LAGG effects on women's decisions to work and work outside the village, are not obtained by random chance because of the correlation of women's outcome within the same caste and/or within the same village.

[Table 9]

[Table 10]

7 Conclusion

In this study, we investigate how various types of peers affect male and female labor market outcomes. Using the information on social relations among individuals in rural India, we uncover the difference in peer effects on labor market outcomes by gender. Female labor supply exhibits strong peer influence regardless of peer types, whereas men's work decisions appear to be unaffected by their peers. We document the relative importance of the social multiplier effect on female labor participation, compared with the social norm effect. Particularly, the aggregate behavior of same-sex peers mainly influence women's work decisions, implying the potential importance of sharing job information among women. Additionally, such a social multiplier effect is present for women's decisions to work outside their village. Given the limited occupational diversity and job opportunities in a village, women tend to work outside the village through job introduction.

Our setting is unique as virtually no work has examined the importance of gender heterogeneity in peer influences on labor market outcomes in the developing country context. The finding is particularly relevant to individuals in developing areas, where communities are weakly inter-connected and individuals' income flows are determined mostly by job opportunities within the community.

Our analysis indicates that policymakers can utilize social network information to improve female welfare in rural communities. Particularly, policy interventions targeting central individuals in social networks may substantially enhance the female labor supply. Although our findings are based on the static data, the LAGG effect on female employment may intrigue interesting future research on short- and long-term social multiplier effects. For instance, suppose policymakers provide employment opportunities to a few women in a village. The policymakers can predict the effect of such policy interventions by tracking how many direct and indirect network neighbors of the women decide to work in the short and long terms.

References

Alesina, A., Giuliano, P., and Nunn, N. (2013). On the origins of gender roles: Women and the plough. *The Quarterly Journal of Economics*, 128(2):469–530.

Assaad, R. (1993). Formal and informal institutions in the labor market, with applications to the construction sector in Egypt. *World Development*, 21(6):925–939.

Ballester, C., Zenou, Y., and Calvó-Armengol, A. (2010). Delinquent networks. *Journal of the European Economic Association*, 8(1):34–61.

Bandiera, O., Barankay, I., and Rasul, I. (2010). Social incentives in the workplace. *The Review of Economic Studies*, 77(2):417–458.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., and Jackson, M. O. (2013). The diffusion of microfinance. *Science*, 341(6144).

Beaman, L., Keleher, N., and Magruder, J. (2018). Do job networks disadvantage women? Evidence from a recruitment experiment in Malawi. *Journal of Labor Economics*, 36(1):121–157.

Benenson, J. F. (1990). Gender differences in social networks. *The Journal of Early Adolescence*, 10(4):472–495.

Blume, L. E., Brock, W. A., Durlauf, S. N., and Jayaraman, R. (2015). Linear social interactions models. *Journal of Political Economy*, 123(2):444–496.

Boucher, V. (2016). Conformism and self-selection in social networks. *Journal of Public Economics*, 136:30–44.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, 150(1):41–55.

Bramoullé, Y. and Kranton, R. (2007). Public goods in networks. *Journal of Economic Theory*, 135(1):478–494.

Calvo-Armengol, A. and Jackson, M. O. (2004). The effects of social networks on employment and inequality. *The American Economic Review*, 94(3):426–454.

Cappellari, L. and Tatsiramos, K. (2015). With a little help from my friends? Quality of social networks, job finding and job match quality. *European Economic Review*, 78:55–75.

Cingano, F. and Rosolia, A. (2012). People I know: Job search and social networks. *Journal of Labor Economics*, 30(2):291–332.

Cornelissen, T., Dustmann, C., and Schönberg, U. (2017). Peer effects in the workplace. *American Economic Review*, 107(2):425–56.

Dharmalingam, A. and Philip Morgan, S. (1996). Women's work, autonomy, and birth control: Evidence from two south Indian villages. *Population Studies*, 50(2):187–201.

Eckstein, Z. and Lifshitz, O. (2011). Dynamic female labor supply. *Econometrica*, 79(6):1675–1726.

Epple, D. and Romano, R. E. (2011). Peer effects in education: A survey of the theory and evidence. In *Handbook of Social Economics*, volume 1, pages 1053–1163. Elsevier.

Fernandez, R. (2007). Women, work, and culture. *Journal of the European Economic Association*, 5(2-3):305–332.

Fernández, R. (2013). Cultural change as learning: The evolution of female labor force participation over a century. *American Economic Review*, 103(1):472–500.

Field, E., Jayachandran, S., and Pande, R. (2010). Do traditional institutions constrain female entrepreneurship? a field experiment on business training in india. *American Economic Review*, 100(2):125–29.

Fletcher, E., Pande, R., and Moore, C. M. T. (2017). Women and work in India: Descriptive evidence and a review of potential policies.

Fogli, A. and Veldkamp, L. (2011). Nature or nurture? learning and the geography of female labor force participation. *Econometrica*, 79(4):1103–1138.

Fulford, S. L. (2015). Marriage migration in India: Vast, varied, and misunderstood. In *International Conference on Migration and Development at Al Akhawayn University in Morocco*.

Gee, L. K., Jones, J. J., Fariss, C. J., Burke, M., and Fowler, J. H. (2017). The paradox of weak ties in 55 countries. *Journal of Economic Behavior & Organization*, 133:362–372.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6):1360–1380.

Hahn, Y., Islam, A., Patacchini, E., and Zenou, Y. (2020). Friendship and female education: Evidence from a field experiment in Bangladeshi primary schools. *The Economic Journal*, 130(627):740–764.

Heath, R. and Tan, X. (2020). Intrahousehold bargaining, female autonomy, and labor supply: Theory and evidence from India. *Journal of the European Economic Association*, 18(4):1928–1968.

Jackson, M., Rodriguez-Barraquer, T., and Tan, X. (2012). Social capital and social quilts: Network patterns of favor exchange. *The American Economic Review*, 102(5):1857–1897.

Jackson, M. O. (2011). An overview of social networks and economic applications. In *Handbook of social economics*, volume 1, pages 511–585. Elsevier.

Jayachandran, S. (2015). The roots of gender inequality in developing countries. *Annual Review of Economics*, 7(1):63–88.

Kramarz, F. and Skans, O. N. (2014). When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies*, 81(3):1164–1200.

Liu, X. and Lee, L.-f. (2010). GMM estimation of social interaction models with centrality. *Journal of Econometrics*, 159(1):99–115.

Liu, X., Patacchini, E., and Zenou, Y. (2014). Endogenous peer effects: local aggregate or local average? *Journal of Economic Behavior & Organization*, 103:39–59.

Manski, C. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3):531.

Maurin, E. and Moschion, J. (2009). The social multiplier and labor market participation of mothers. *American Economic Journal: Applied Economics*, 1(1):251–72.

Mehrotra, S. and Parida, J. K. (2017). Why is the labour force participation of women declining in India? *World Development*, 98:360–380.

Mota, N., Patacchini, E., and Rosenthal, S. S. (2016). Neighborhood effects, peer classification, and the decision of women to work.

Munshi, K. and Rosenzweig, M. (2006). Traditional institutions meet the modern world: Caste, gender, and schooling choice in a globalizing economy. *American Economic Review*, 96(4):1225–1252.

Nicoletti, C., Salvanes, K. G., and Tominey, E. (2018). The family peer effect on mothers' labor supply. *American Economic Journal: Applied Economics*, 10(3):206–34.

Patacchini, E., Rainone, E., and Zenou, Y. (2017). Heterogeneous peer effects in education. *Journal of Economic Behavior & Organization*, 134:190–227.

Patacchini, E. and Zenou, Y. (2012). Juvenile delinquency and conformism. *The Journal of Law, Economics, & Organization*, 28(1):1–31.

Schmutte, I. M. (2014). Free to move? A network analytic approach for learning the limits to job mobility. *Labour Economics*, 29:49–61.

Songsermsawas, T., Baylis, K., Chhatre, A., and Michelson, H. (2016). Can peers improve agricultural revenue? *World Development*, 83:163–178.

World Economic Forum (2017). The Global Gender Gap Report. World Economic Forum.

Tables and figures

Table 1: Summary statistics

Variable	All Mean	All SD	Male Mean	Male SD	Female Mean	Female SD
Age	39.0	12.7	43.6	12.3	35.3	11.7
Education	5.03	4.66	5.65	4.57	4.54	4.67
General caste	0.123	0.329	0.128	0.334	0.119	0.324
Village native	0.559	0.497	0.908	0.289	0.278	0.448
Hindu	0.958	0.201	0.958	0.201	0.958	0.201
Kannada	0.225	0.418	0.232	0.422	0.220	0.414
Work	0.630	0.483	0.877	0.328	0.431	0.495
Work outside village	0.213	0.41	0.353	0.478	0.101	0.301
N	16,484		7,195		9,289	

Data: Social Networks and Microfinance
SD indicates the standard deviation.

Table 2: Number of network neighbors by peer types

	All			Male			Female		
	Degree	Male	Female	Degree	Male	Female	Degree	Male	Female
Friends	8.11	45.2%	54.8%	8.43	59.4%	40.6%	7.86	33.7%	66.3%
Relatives	7.27	51.7%	48.3%	8.01	40.9%	59.1%	6.69	63.3%	36.7%
Risk sharing	8.51	46.1%	53.9%	8.93	59.0%	41.0%	8.18	35.2%	64.8%

Data: Social Networks and Microfinance

Table 3: Summary statistics for local average and local aggregate peer outcomes

	Male		Female	
	Proportion of peers who work	Aggregate number of peers who work	Proportion of peers who work	Aggregate number of peers who work
Friends	0.679	3.021	0.603	2.380
	(0.274)	(2.148)	(0.284)	(1.629)
Relatives	0.587	2.449	0.720	2.052
	(0.311)	(1.946)	(0.308)	(1.427)
Risk sharing	0.682	3.268	0.615	2.513
	(0.267)	(2.312)	(0.282)	(1.714)
	Proportion of peers who work outside the village	Aggregate number of peers who work outside the village	Proportion of peers who work outside the village	Aggregate number of peers who work outside the village
Friends	0.232	1.021	0.196	0.727
	(0.255)	(1.211)	(0.256)	(0.939)
Relatives	0.184	0.782	0.269	0.720
	(0.250)	(1.099)	(0.336)	(0.908)
Risk sharing	0.231	1.089	0.201	0.774
	(0.251)	(1.293)	(0.257)	(0.997)

Data: Social Networks and Microfinance
Standard deviations are in parentheses.

Table 4: Local average peer effect (social norm) on decisions to work

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
** Panel A: OLS*						
Peer effect						
Proportion of peers who work	0.098***	0.056***	0.105***	0.176***	0.145***	0.192***
	(0.018)	(0.016)	(0.021)	(0.026)	(0.020)	(0.025)
Own characteristics						
Age	0.020***	0.020***	0.020***	0.056***	0.058***	0.056***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education	0.008***	0.008***	0.008***	-0.023***	-0.021***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
General Caste	-0.014	-0.030	-0.007	-0.074**	-0.048	-0.075***
	(0.024)	(0.042)	(0.027)	(0.028)	(0.039)	(0.028)
Village native	0.002	0.001	0.002	0.078***	0.076***	0.080***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Hindu	0.036	0.035	-0.010	0.103**	0.174***	0.125**
	(0.026)	(0.059)	(0.042)	(0.047)	(0.046)	(0.049)
Kannada	0.006	0.004	0.005	0.023	0.022	0.033*
	(0.011)	(0.012)	(0.011)	(0.017)	(0.017)	(0.019)
Age^2	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education^2	-0.000**	-0.000**	-0.000**	0.001**	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
** Panel B: 2SLS*						
Peer effect						
Proportion of peers who work	0.054	-0.020	0.084	0.094	0.162***	0.089
	(0.072)	(0.064)	(0.072)	(0.090)	(0.059)	(0.094)
Own characteristics						
Age	0.021***	0.021***	0.020***	0.056***	0.058***	0.056***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education	0.008***	0.007***	0.008***	-0.023***	-0.022***	-0.023***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)
General Caste	-0.015	-0.028	-0.007	-0.073**	-0.048	-0.078***
	(0.023)	(0.041)	(0.026)	(0.028)	(0.039)	(0.028)
Village native	0.003	0.003	0.002	0.075***	0.077***	0.077***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)
Hindu	0.035	0.021	-0.011	0.089*	0.179***	0.111**
	(0.026)	(0.062)	(0.042)	(0.051)	(0.047)	(0.052)
Kannada	0.006	0.005	0.005	0.023	0.022	0.032*
	(0.011)	(0.012)	(0.010)	(0.017)	(0.017)	(0.018)
Age^2	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education^2	-0.000**	-0.000**	-0.000**	0.001**	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-stat	20.88	20.00	21.83	28.62	58.60	24.67
Anderson–Rubin F-stat	0.91	2.49	1.83	1.71	4.37	1.28
Anderson–Rubin p-value	[0.56]	[0.00]	[0.04]	[0.06]	[0.00]	[0.23]
N	7,195	7,195	7,195	9,289	9,289	9,289
Mean dependent variable	0.896	0.896	0.896	0.432	0.432	0.432

Column headings show types of peer relations. Peer variables are the average outcome of peers in the network of the corresponding type. Peers' average characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, education^2), and village fixed effects are controlled for. Standard errors are in parentheses and clustered at the village level.
***p< 0.01, **p< 0.05, *p< 0.1

Table 5: Local aggregate peer effect (social multiplier) on decisions to work

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
** Panel A: OLS*						
Peer effects						
Number of peers who work	0.034***	0.019***	0.033***	0.056***	0.058***	0.059***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)
Own characteristics						
Age	0.019***	0.020***	0.020***	0.055***	0.056***	0.056***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education	0.008***	0.008***	0.008***	-0.024***	-0.024***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
General caste	0.001	0.019	0.011	-0.080***	-0.090***	-0.071**
	(0.019)	(0.024)	(0.021)	(0.027)	(0.030)	(0.030)
Village native	0.004	0.004	0.004	0.082***	0.082***	0.083***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)
Hindu	0.010	-0.007	0.008	0.096**	0.136***	0.129***
	(0.023)	(0.028)	(0.023)	(0.037)	(0.040)	(0.039)
Kannada	0.009	0.020*	0.016	0.031*	0.036**	0.037**
	(0.011)	(0.011)	(0.011)	(0.018)	(0.018)	(0.018)
Age^2	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Education^2$	-0.000**	-0.000**	-0.000**	0.001**	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
** Panel B: 2SLS*						
Peer effects						
Number of peers who work	0.008	-0.005	-0.005	0.103***	0.106***	0.073***
	(0.013)	(0.013)	(0.015)	(0.011)	(0.021)	(0.014)
Own characteristics						
Age	0.021***	0.021***	0.022***	0.055***	0.056***	0.056***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education	0.008***	0.007***	0.007***	-0.024***	-0.024***	-0.023***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
General Caste	-0.002	0.020	0.007	-0.086***	-0.096***	-0.073**
	(0.019)	(0.024)	(0.020)	(0.027)	(0.030)	(0.030)
Village native	0.006	0.004	0.003	0.087***	0.087***	0.084***
	(0.015)	(0.016)	(0.015)	(0.013)	(0.014)	(0.013)
Hindu	0.000	-0.023	-0.014	0.125***	0.162***	0.137**
	(0.023)	(0.029)	(0.026)	(0.037)	(0.040)	(0.039)
Kannada	0.010	0.020*	0.017	0.031*	0.036**	0.037**
	(0.011)	(0.011)	(0.011)	(0.018)	(0.018)	(0.018)
Age^2	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Education^2$	-0.000**	-0.000**	-0.000**	0.001**	0.001**	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-stat	40.39	42.81	31.42	45.31	61.46	42.68
Anderson–Rubin F-stat	1.70	0.56	0.99	21.15	13.04	9.82
Anderson–Rubin p-value	[0.07]	[0.91]	[0.48]	[0.00]	[0.00]	[0.00]
N	7,195	7,195	7,195	9,289	9,289	9,289
Mean dependent variable	0.896	0.896	0.896	0.432	0.432	0.432

Column headings show the types of peer relations. Peer variables are the aggregate outcome of peers in the network of the corresponding type. Peers' average characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, $education^2$), and village fixed effects are controlled for. Standard errors are in parentheses and clustered at the village level.

***p< 0.01, **p< 0.05, *p< 0.1

Table 6: Unified framework on decisions to work: 2SLS results

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
LAVG effect	-0.039	0.011	0.034	-0.227*	-0.062	-0.215
	(0.070)	(0.087)	(0.080)	(0.118)	(0.088)	(0.143)
LAGG effect	0.012	-0.006	0.007	0.107***	0.092***	0.089***
	(0.013)	(0.015)	(0.014)	(0.019)	(0.028)	(0.020)
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-stat	11.82	9.43	12.24	17.34	26.82	14.84
Anderson–Rubin F-stat	4.60	5.55	3.50	3.56	3.38	3.10
Anderson–Rubin p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	7,195	7,195	7,195	9,289	9,289	9,289
Mean dependent variable	0.896	0.896	0.896	0.432	0.432	0.432

Column headings show the types of peer relations. Peer variables are the average and aggregate outcomes of peers in the network of the corresponding type. Control variables include individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, education^2), peers' average and aggregate characteristics, and village fixed effects. Standard errors are in parentheses and clustered at the village level.
***p< 0.01, **p< 0.05, *p< 0.1

Table 7: Gender specific peer effects on decisions to work: 2SLS results

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
** Panel A: LAVG effects*						
Male peers	0.007	-0.059	-0.004	-0.009	0.016	0.028
	(0.070)	(0.040)	(0.042)	(0.078)	(0.072)	(0.082)
Female peers	0.062	0.094	0.130*	0.134*	0.089	0.113
	(0.058)	(0.071)	(0.066)	(0.079)	(0.066)	(0.076)
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-stat	4.34	5.45	4.46	12.53	10.70	11.92
Anderson–Rubin F-stat	2.86	2.41	2.06	1.79	4.31	1.60
Anderson–Rubin p-value	[0.00]	[0.00]	[0.01]	[0.02]	[0.00]	[0.05]
** Panel B: LAGG effects*						
Male peers	0.011	-0.019	-0.008	0.035	0.026	0.014
	(0.022)	(0.027)	(0.080)	(0.018)	(0.030)	(0.041)
Female peers	0.034**	0.015	0.017	0.140***	0.158***	0.108***
	(0.016)	(0.013)	(0.014)	(0.013)	(0.020)	(0.016)
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-statistics	23.22	16.56	18.28	23.59	21.75	15.98
Anderson–Rubin F-stat	3.32	1.03	1.72	18.46	12.46	12.09
Anderson–Rubin p-value	[0.00]	[0.45]	[0.03]	[0.00]	[0.00]	[0.00]
N	7,195	7,195	7,195	9,289	9,289	9,289
Mean dependent variable	0.896	0.896	0.896	0.432	0.432	0.432

Column headings show the types of peer relations. Peer variables are the average or aggregate outcome of male and female peers in the network of the corresponding type. Control variables include individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, education^2), peers' average or aggregate characteristics, and village fixed effects. Standard errors are in parentheses and clustered at the village level.

***p< 0.01, **p< 0.05, *p< 0.1

Table 8: Unified framework of peer effects on decision to work outside villages (all individuals): 2SLS results

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
LAVG effect	0.748***	0.367	0.469**	0.025	0.033	-0.016
	(0.204)	(0.242)	(0.220)	(0.104)	(0.060)	(0.106)
LAGG effect	-0.025	0.067	0.054	0.062**	0.024	0.068***
	(0.032)	(0.046)	(0.036)	(0.021)	(0.018)	(0.021)
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-statistics	5.83	5.39	7.99	9.12	10.42	9.94
Anderson–Rubin F-stat	4.60	5.55	3.50	3.56	3.38	3.10
Anderson–Rubin *p*-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	7,195	7,195	7,195	9,289	9,289	9,289
Mean dependent variable	0.365	0.365	0.365	0.102	0.102	0.102

Column headings show the types of peer relations. Peer variables are the average and aggregate outcomes of peers in the network of the corresponding type. Control variables are individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, $education^2$), peers' average and aggregate characteristics, and village fixed effects. Standard errors are in parentheses and clustered at the village level.
***p< 0.01, **p< 0.05, *p< 0.1

Table 9: Falsification tests: work

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
** Panel A: Fictitious friends randomly chosen from the same village*						
Mean of LAVG peer effects	0.003	-0.001	-0.014	0.008	0.027	-0.019
Mean of standard errors	(0.325)	(0.250)	(0.337)	(0.521)	(0.347)	(0.489)
Proportion of significant simulations	1%	0%	2%	2%	2%	1%
Mean of LAGG peer effects	-0.001	-0.001	0.000	-0.009	-0.008	-0.006
Mean of standard errors	(0.047)	(0.042)	(0.045)	(0.068)	(0.064)	(0.061)
Proportion of significant simulations	3%	1%	4%	1%	3%	1%
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
** Panel B: Fictitious friends of the same caste within the same village*						
Mean of LAVG peer effects	-0.034	-0.023	-0.014	-0.026	-0.027	-0.016
Mean of standard errors	(0.173)	(0.124)	(0.180)	(0.280)	(0.221)	(0.269)
Proportion of significant simulations	1%	0%	2%	2%	1%	3%
Mean of LAGG peer effects	0.011	0.008	0.003	0.008	0.012	0.006
Mean of standard errors	(0.053)	(0.041)	(0.049)	(0.085)	(0.078)	(0.075)
Proportion of significant simulations	3%	0%	2%	2%	3%	4%
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
N	7,195	7,195	7,195	9,289	9,289	9,289

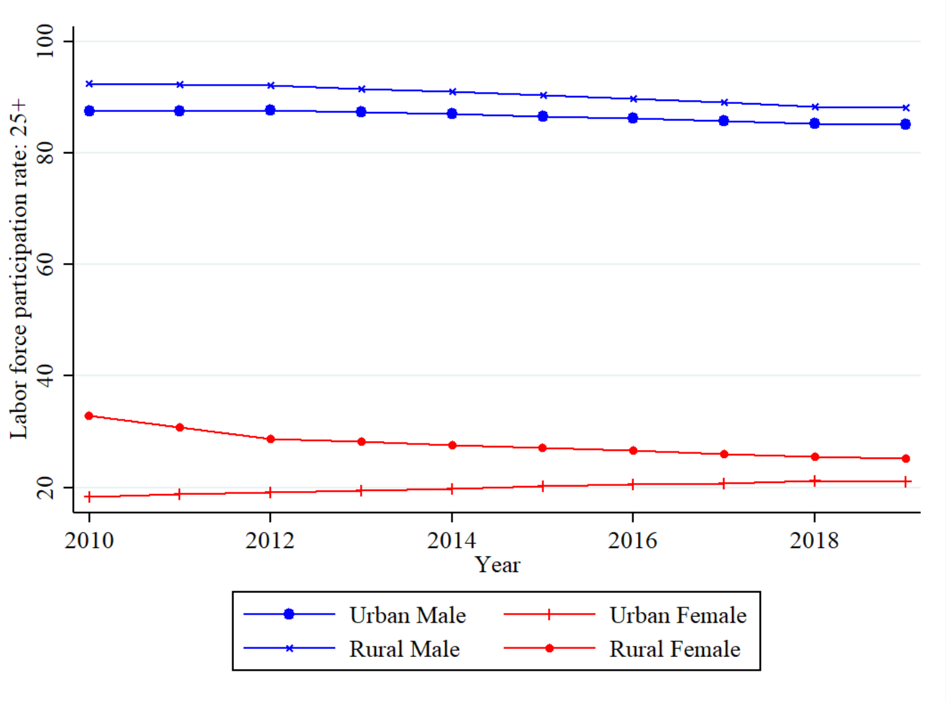
We report the average results from a total of 100 simulations. Column headings show the types of peer relations. Peer variables are the average and aggregate outcomes of peers in the network of the corresponding type. Control variables are individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, education^2), peers' average and aggregate characteristics, and village fixed effects. Standard errors (the average from the 100 simulations) are in parentheses and clustered at the village level. The proportion of significant simulations indicates the fraction of simulations in which the coefficient estimate is statistically significant at the 5% level.

Table 10: Falsification tests: work outside the village

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
** Panel A: Fictitious friends randomly chosen from the same village*						
Mean of LAVG peer effects	0.080	-0.006	0.030	-0.007	0.006	0.000
Mean of standard errors	(0.588)	(0.463)	(0.590)	(0.347)	(0.266)	(0.350)
Proportion of significant simulations	3%	1%	2%	3%	1%	5%
Mean of LAGG peer effects	-0.017	-0.002	-0.013	0.001	0.001	-0.001
Mean of standard errors	(0.076)	(0.077)	(0.071)	(0.044)	(0.045)	(0.041)
Proportion of significant simulations	0%	1%	0%	2%	2%	0%
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
** Panel B: Fictitious friends of the same caste within the same village*						
Mean of LAVG peer effects	0.028	-0.040	-0.002	-0.015	0.007	0.007
Mean of standard errors	(0.317)	(0.276)	(0.323)	(0.194)	(0.168)	(0.195)
Proportion of significant simulations	0%	0%	1%	3%	1%	3%
Mean of LAGG peer effects	-0.006	0.011	-0.002	-0.001	-0.005	-0.005
Mean of standard errors	(0.085)	(0.095)	(0.080)	(0.051)	(0.056)	(0.047)
Proportion of significant simulations	1%	4%	1%	1%	1%	5%
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
N	7,195	7,195	7,195	9,289	9,289	9,289

We report the average results from a total of 100 simulations. Column headings show the types of peer relations. Peer variables are the average and aggregate outcomes of peers in the network of the corresponding type. Control variables are individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, $education^2$), peers' average and aggregate characteristics, and village fixed effects. Standard errors (the average from the 100 simulations) are in parentheses and clustered at the village level. The proportion of significant simulations indicates the fraction of simulations in which the coefficient estimate is statistically significant at the 5% level.
***$p< 0.01$, **$p< 0.05$, *$p< 0.1$

Figure 1: Labor force participation rate (population aged 25 years and above) in India



Source: ILOSTAT. https://ilostat.ilo.org/

Appendix

Table A1: Unified framework of gender-specific peer effects on decision to work: IV results

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
Male peers' LAVG effect	-0.006	0.013	0.067	-0.021	0.115	0.074
	(0.084)	(0.085)	(0.076)	(0.149)	(0.108)	(0.147)
Male peers' LAGG effect	0.013	-0.006	-0.025	0.009	-0.048	-0.039
	(0.038)	(0.051)	(0.030)	(0.084)	(0.055)	(0.090)
Female peers' LAVG effect	0.018	0.081	0.120	-0.049	-0.104	-0.055
	(0.075)	(0.093)	(0.076)	(0.104)	(0.087)	(0.111)
Female peers' LAGG effect	0.026	-0.004	-0.001	0.131***	0.169***	0.114***
	(0.022)	(0.021)	(0.020)	(0.025)	(0.027)	(0.027)
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-stat	2.65	2.81	2.52	6.50	5.59	6.48
Anderson–Rubin F-stat	11.60	7.78	8.93	25.37	18.30	12.07
Anderson–Rubin p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	7,195	7,195	7,195	9,289	9,289	9,289
Mean dependent variable	0.896	0.896	0.896	0.432	0.432	0.432

Column headings show the types of peer relations. Peer variables are the average and aggregate outcomes of male and female peers in the network of the corresponding type. Control variables include individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, $education^2$), peers' average and aggregate characteristics, and village fixed effects. Standard errors are in parentheses and clustered at the village level.
***p< 0.01, **p< 0.05, *p< 0.1

Table A2: Unified framework of peer effects on decision to work outside villages (sample: individuals who worked last week): 2SLS results

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer type	Friends	Relatives	RS	Friends	Relatives	RS
LAVG effect	0.889***	0.443*	0.471**	0.234	0.023	-0.138
	(0.218)	(0.265)	(0.234)	(0.204)	(0.129)	(0.199)
LAGG effect	-0.026	0.055	0.066	0.108**	0.086**	0.145***
	(0.033)	(0.049)	(0.042)	(0.043)	(0.034)	(0.047)
Own characteristics	YES	YES	YES	YES	YES	YES
Peers' characteristics	YES	YES	YES	YES	YES	YES
Village fixed effects	YES	YES	YES	YES	YES	YES
Cragg–Donald F-stat	5.46	5.03	7.45	4.43	4.71	6.42
Anderson–Rubin F-stat	4.78	7.02	3.66	4.12	3.92	2.98
Anderson–Rubin *p*-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	6,447	6,447	6,447	4,015	4,015	4,015
Mean dependent variable	0.408	0.408	0.408	0.235	0.235	0.235

Column headings show the types of peer relations. Peer variables are the average and aggregate outcomes of male and female peers in the network of the corresponding type. Control variables are individual characteristics (age, education, general caste, village native, Hindu, Kannada, age^2, education^2), peers' average and aggregate characteristics, and village fixed effects. Standard errors are in parentheses and clustered at the village level.

***p< 0.01, **p< 0.05, *p< 0.1