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Abstract

This paper uses primary data on women's social networks to estimate causal peer effects in the household bargain. Using an extension of a spatial weighting technique that relies on friends-of-friends to identify peer effects, we examine how a woman's friends' participation in an education program affects her physical mobility, access to outside employment, and probability of working outside the household, as well as her children's food consumption. Results show that peer effects have a significant impact on all proxies of female bargaining power. We decompose the overall peer effects into those on participants and non-participants, and focus on the effects on non-participant women who have participant friends. Results are consistent with the weak directionality assumption required for the identification of causal peer effects that participants inform and empower their non-participants friends, and not the other way around. Then, using household fixed effects, we find an overall positive effect of the mother's participant friends on children's food consumption. In particular, we find that the sons and daughters of non-participants who have participant friends eat more similar diets than sons and daughters of non-participants who have no participant friends. Finally, in heterogeneity analysis, we combine the Nash bargaining framework with demographic diffusion literature and identity economics to define and provide suggestive empirical evidence on three ways in which networks affect household decision making: (1) information, (2) influence, and (3) identity. While this analysis refrains from making welfare conclusions, our results highlight the presence of significant and complex peer effects in the household bargain.

JEL Codes: D13, D85, J13, O15

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1.1 Motivation

Peer effects have been extensively examined in the context of informational spillovers (Kohler et al., 2001; Conley and Udry, 2010; Miguel and Kremer, 2004; Foster and Rosenzweig, 1995; Oster and Thornton, 2012), but their impact on social norm-driven behaviors, whether negative or positive, is less well understood, particularly outside the context of health-seeking behavior adoption (Munshi and Myaux, 2006; Christakis and Fowler, 2008; Lundborg, 2006). Some outcomes appear very difficult to alter: female household bargaining power and child malnutrition in India are two classic examples that don't necessarily change with health interventions (Das Gupta et al., 2005), increases in income (Haddad et al., 2003) or even access to information Kabeer (1999). On the other hand, increasing evidence suggests that these very outcomes change rapidly under changing social norms or expectations (Munshi and Myaux, 2006; Jensen and Oster, 2009; Chong and La Ferrara, 2009; La Ferrara et al., 2012). Female bargaining power is thus one area where peers, by changing social norms, may be expected to play a large role.

In this paper, we ask whether through social networks, peers affect female bargaining power and children's food consumption. Women tend to invest more in their children than do fathers, and more empowered women invest more equally in their sons and daughters than do less empowered women (Oster, 2009; Beegle et al., 2001; Rosenzweig and Schultz, 1982; Maitra, 2004; Thomas et al., 2002; Quisumbing and de la Brière, 2000). Therefore, evidence that the daughters of women with empowered friends have a higher quality diet than daughters of women without empowered friends would suggest that peer effects influence children's food consumption through the household bargain. Further, we explore whether peer effects work through information or influence. We use snowball sampling to collect primary data on self-reported networks, female empowerment, and child nutrition from the state of Uttarakhand in the Indian Himalayas. We identify a shock to female bargaining power and social networks using a government program called *Mahila Samakhya*. This program aims to increase female empowerment through education and has been in place in Uttarakhand since 1995, but was rapidly and randomly scaled up between 2004 and 2008. Our sample consists of 487 women and their friends from 69 randomly-chosen villages, stratified into districts, four with the program and two without. All villages in this sample received the program in the expansionary stage. We ask how peers' bargaining power affects the intrahousehold bargaining power of other women in their network.

In the demographic diffusion literature, *social learning* and *social influence* describe how individuals act on information acquired from peers (Montgomery and Casterline, 1996; Munshi and Myaux, 2006). For example, social learning occurs when women obtain information about contraceptive methods from peers and family. Social networks provide information and help individuals gauge the quality of the information (Kohler et al., 2001). Social influence occurs when individuals act in similar ways to avoid conflict within the social group. Influence can also work through identity, providing examples to encourage individuals to copy peers' behavior (Behrman et al., 2002) as well as the set of peers relative to whom we define our well-being (Akerlof, 1980).

Peer networks provide their members information about employment opportunities (Munshi and Rosenzweig, 2006), supply marital partners (Banerjee et al., 2009), and facilitate adoption of new technologies (Conley and Udry, 2010). How peer networks influence social norms is less well understood. Homophily-induced homogeneous networks may limit the network's ability to affect social norms or at least delay the process, since both information and social norms are likely already common to the network, and may well be reinforced instead of challenged by network connections. Indeed, economists have found both theoretical and empirical evidence suggesting that homophily slows social learning and therefore convergence in the adoption of new technologies (Behrman et al., 2002; Golub and Jackson, 2012, 2010).

A woman's ability to influence household resource allocation depends not only on the information available to her but also on her bargaining power, the social norms,[1] her notion of identity and the utility she receives from it,[2] as well as the interactions of these forces. In addition to learning new information from peers, individuals may also want to emulate friends and define their well-being relative to their peers. Friends thus not only provide information but also directly influence behavior, thus helping define identity. Identity and social capital can be a source of strength and confidence (Sen, 2006) but in the presence of constricting social norms, identity can confine and limit power. Peer networks in traditional societies may be homogenous and stratified by income or social hierarchy, therefore reinforcing social norms. Conservative social norms will reinforce current bargaining power patterns (Hoff and Pandey, 2006; Mayoux, 2001), which are often skewed to the male in the household. It is thus important to understand how peer effects, whether negative or positive, affect norm-driven household behavior.

To study whether peer networks influence bargaining power and therefore child welfare, we test the following hypotheses: (1) Does the bargaining power of a woman's peers affect her own bargaining power? (2) Do social learning and influence cause networks to change a woman's parenting behavior? We develop a utility maximization model where consumption smoothing gives parents an economic incentive to invest in their children. This incentive may be larger for women who face lower future income prospects than their husbands. Peers affect a woman's allocation decision in three ways: first, support groups increase her disagreement utility, and allow her greater control of household resources.[3] Second, learning from friends

[1] A social norm refers to the behavioral expectations within society or a sub-group of society. Norms "coordinate people's expectations in interactions that possess multiple equilibria" (Durlauf and Blume, 2008).

[2] Identity utility is the "gain when actions conform to actions and ideals, and the loss insofar as they do not" (Akerlof and Kranton, 2010, p. 18).

[3] Disagreement or threat-point utility refers to the utility each adult receives if the household bargain fails and cooperation breaks down (Mas-Colell et al., 1995, p. 839).

removes constraints placed by social norms, allowing the woman a greater range of choices. Third, belonging to networks causes a woman to be influenced by her friends' choices and gain utility from mimicking their actions, which in turn may increase or decrease her say in her household's decision making process.

We examine how a woman's friends' participation in *Mahila Samakhya* affects four dimensions of household decision making: (1) the woman's physical mobility, (2) her access to outside employment and (3) likelihood of working outside the household, as well as (4) her children's food consumption.[4] We address concerns about identifying peer effects in the presence of reflection, and endogenous program participation and network formation. We use an extension of a spatial weighting technique that relies on friends of friends to identify peer effects over these four dimensions of household decision making, while also instrumenting for group formation and program participation. Results show that having empowered peers significantly improves women's physical mobility and access to outside employment. Further, using household fixed effects, we find that women with more empowered friends feed their daughters a more protein-rich diet than women with fewer empowered friends, which is indicative of a peer effect that works through the intrahousehold bargain. We also develop a conceptual framework that combines the Nash bargaining framework with the demographic diffusion literature (Montgomery and Casterline, 1996) and identity (Akerlof and Kranton, 2010) to define some potential channels through which peer effects work: information, influence and identity (the last being a specific form of influence). Finally, we provide suggestive empirical evidence of these channels by allowing the causal peer effect to vary in the characteristics of the woman. We find that, while the direct effects of participation in *Mahila Samakhya* are largely driven by influence, the peer effects on non-participants largely act through information.

The contributions of this paper are as follow: first, we quantify the effect of peer networks on household decision making suggesting the presence of peer effects on social norms. Second, our estimates relax the commonly-made but restrictive assumption of separability of group formation and information flows by accounting for endogenous group formation. Better understanding network formation may be particularly important for policy design because several policy instruments rely on altering network formation to enhance impact. Third, we also relax the equally restrictive assumption of directed networks by estimating the impact of a participant friend's empowerment on non-participant friends. The directionality assumption is key to identification in the presence of the reflection problem but can lead to significant overestimates. Since we are able to isolate the marginal effect of friends' participation on non-participants, our identifying assumption is that participant friends inform and influence their non-participant friends. Fourth, we define and provide

[4]Note that the first three of these dimensions, physical mobility, access to outside employment and actually working outside the household, are both proxies for and outcomes of empowerment, while the fourth, children's food consumption, is a pure outcome. By considering both proxies for and outcomes of empowerment, we aim to capture the range of peer effects in household decision making.

suggestive evidence on three potential channels through which peer effects may work in household decision making: social information and influence.

Understanding the role of peer effects in determining female bargaining power and children's food consumption helps us better understand the determinants of household decision making. While it has been shown that empowering women can improve child outcomes, the factors determining female bargaining power are not fully understood. If peer networks affect bargaining power and child outcomes, whether positively or negatively, they need to be accounted for when designing and evaluating development programs. Understanding this relationship among peers, female empowerment and child outcomes may allow for a better targeting of development programs to harness the potential multiplier effects delivered through social networks.

2 Uttarakhand and The *Mahila Samakhya* Program

Following decades of local demand for a separate state, Uttarakhand was carved out of the state of Uttar Pradesh in November 2000. Small, scattered villages without access to roads pose challenges to the state's development. Most villages are remote and many lack basic infrastructure such as schools and hospitals. Households generally engage in subsistence-type agriculture, although the state also supplies migrant labor to Delhi and other large towns. The literacy rate in Uttarakhand is 72 percent, lower than the national average of 80 percent. However, the state is also relative wealthy: in 2005-06, only eight percent of Uttarakhand households fell in the poorest wealth quintile nationally (IIPS and ORC Macro, 2007).

Uttarakhand has a large Hindu population— 85 percent as compared to 80 percent for the entire country (Census of India, 2001), with 18 percent belonging to Scheduled Castes and Tribes.[5] Caste hierarchy is strictly maintained in Uttarakhandi villages, and most interactions are limited to members of the same caste. Villages are clusters of houses that are isolated from other villages by the hilly terrain, further limiting contact with others.

Alcoholism and domestic violence are common problems in Uttarakhand; almost forty percent of Uttarakhandi men consume alcohol, compared to the national average of 32 percent, and more than a quarter (26 percent) of all Uttarakhandi women have experienced physical violence (IIPS and ORC Macro, 2007). Only 18 percent of these women— or about five percent of the overall population— have sought help to control or end the violence. Uttarakhandi women also tend to have few social interactions outside the immediate family. Firewood and water collection are women's tasks and often consume more than half the day. The remoteness of the region and lack of good roads combined with stringent social norms mean that once married, women are unable to visit friends or even parents regularly. As many as 47 percent of Uttarakhandi

[5] The Constitution of India categorizes the lower castes and tribes as Scheduled Castes and Tribes and provides them special protections and rights to help overcome the effects of discrimination by higher castes.

women reported not having the final say on visits to family and friends (IIPS and ORC Macro, 2007). Field tests and the data suggest that women's lives are defined by their husbands, children, and in-laws, and they seldom participate in the political process, even at the village level. Constricting social norms thus restrict women to the narrow spheres of family and housework.

2.1 *Mahila Samakhya* in Uttarakhand

Mahila Samakhya is a women's empowerment program that started in 1995 in what is now Uttarakhand. The program covers 2,416 villages in six of thirteen of Uttarakhandi districts. More than 42,000 women participate in this program, and over 2,500 girls have been educated in its centers. The program focuses on formal and informal education as the means to empowerment. Literacy camps, adult education centers, and vocational training enable participants to earn an income primarily through artisanry and store-keeping. In addition, the program provides special education on resolving domestic disputes and conflicts within the community. Program rollout is not always straightforward. Local men sometimes resist the program and prevent their wives from participating. As a result, initially only a few women may participate, but as others see the benefits of participation, they muster up the courage to participate despite family opposition. Further, as the husbands and in-laws see the benefits of participation, particularly through enhanced employability and increases in household income, they reduce opposition to the program over time.

Mahila Samakhya enters a village through program workers called *sahayoginis* who begin by talking with women in the village to determine their needs and possible objectives for the program. Thus, the actual form of the program varies from village to village, although most begin with an education or literacy camp. Nominally, the program targets districts with likely low rates of female bargaining power, identified through lower-than-average rates of female education, low school attendance by girls, remoteness and lack of development. In practice, we find few significant differences in exogenous characteristics of our sample of women in treated versus control districts. Using block-level data on village-level female bargaining power from Indian censuses before the program in 1991 and 2001, we find no significant differences in blocks which later received *Mahila Samakhya* with those that did not. Using the nationally-representative NFHS-3 and DLHS-3, we find that women in untreated districts in our sample do not differ significantly from those in the state at large. This lack of a significant difference supports the assumption that the program is not targeted to pre-existing levels of female bargaining power. (For more details, see Kandpal et al. (2013).)

Village- and district-level meetings allow participants to step outside their homes and villages, introducing them to a more diverse set of peers. Participants meet women from other castes and religions, which expands their peer networks and lets them engage in conversation not pertaining to domestic chores and family (Kandpal and Baylis, 2013). The semi-formal and well-structured nature of these interactions facilitates dialogue. The information provided by *Mahila Samakhya* as well as that exchanged within the newly-expanded networks may help change social norms. The learned vocational skills allow participants to engage in income-generating activities. In particular, respondents are encouraged to acquire identification cards that enable them to participate in the government's National Rural Employment Guarantee Scheme (NREGS). NREGS guarantees at least a hundred days of paid work to the rural poor. By providing an income and increasing physical mobility, participation in NREGS increases womens' household bargaining power, which may change local norms over time. Few other papers study *Mahila Samakhya* but they find positive impacts on female empowerment and social capital from participation in the program (Janssens, 2010; Kandpal et al., 2013). Finding evidence that Mahila Samakhya helps empower rural women by providing them better access to the NREGS scheme, as well as increasing their physical mobility and political participation, Kandpal et al. (2013) further attempt to disentangle the program's mechanisms, separately considering its effect on women who work, and those who do not work but whose reservation wage is increased by participation; however, the authors do not estimate peer effects of participation in *Mahila Samakhya*. They find consistent estimates for average treatment and intent to treat effects.

3 Model

We hypothesize that *Mahila Samakhya* has two effects on female empowerment: one is the intended treatment effect of the program on participants, and the other is the peer effect that may affect non-participants as well as participants. The program treatment effect works through education, while the peer effect works through social network spillovers between participants and their participant and non-participant friends. Having participant friends may, for instance, expand the perceived feasible set of household bargaining outcomes for participants and non-participants. Through support from more empowered friends, this indirect effect may enable even non-participants to improve their bargaining outcomes such as being able to allocate more resources to their children. As more and more women are directly or indirectly affected by the program, *Mahila Samakhya* may indeed change the norm faced by all women in the village. The effect of participation in *Mahila Samakhya* can thus be summarized as follows: the program exposes women to new information, leading to social learning, and works through social influence to ease constraints placed by norms as well as increase the identity utility received from belonging to a more empowered network.

In this section, we present a modified Nash bargaining model to describe the potential causal mechanisms through which *Mahila Samakya* may affect outcomes. Economists often argue that since mothers invest more in their children than do fathers, men and women have inherently different preferences with regard to household resource allocation, and that as a result, bargaining power affects the allocation of household resources as well as labor supply decisions (Ghosh and Kanbur, 2008; Agarwal, 2001; Sahn and Stifel, 2002; Quisumbing and de la Brière, 2000). A woman with little bargaining power within the household gets a smaller share of the household's resources than a woman with more bargaining power (Phipps and Burton, 1998; Thomas, 1990). Further, household resource allocations can vary significantly depending on who makes the decisions: men spend more money on personal consumption while women channel a larger share to their children's education and health (Kanbur and Haddad, 1994). Rather than assume that women are more altruistic than men, our causal model provides women an economic incentive to invest in their children. Second, our model explicitly describes the effect of peer networks on bargaining power and child welfare.

To start, we model the husband and wife as playing a two-period cooperative Nash bargaining game. If the bargain breaks down, the husband and wife each receive disagreement utility, which is lower than what they would have received if the bargain had been successful (McElroy, 1990; Lundberg and Pollak, 1996). The standard household Nash bargaining model does not account for the role of networks in determining disagreement utility, nor for the effects of identity utility or social learning and influence on the outcome of the bargain. The disagreement utility is simply each spouse's intertemporal utility had they remained single or non-cooperative in marriage; this utility depends on each spouse's earning potential and on the non-cooperative equilibrium outcome of investment in children.

To incorporate networks into the Nash bargaining model, first, we model the adults as making a joint decision by maximizing the generalized Nash product, $\mathbf{x}$, which comprises a private good c, leisure l, and a public good, r, reflecting investment in children. Each adult's say in the household is represented by the exponents α and β, which sum to one and reflect the relative levels of bargaining power captured by husband and wife. These exponents can change over time to reflect changing social norms. The bargain leads to optimal values of the bundle for each adult, $\mathbf{x}^*$. These consumption bundles belong to a set $\{X\}$ of all possible choices of $\mathbf{x}$. In period one, the adults choose their optimal $\mathbf{x}$ for the first time period to maximize the current period utility and expected utility in the next time period.

To model constraints imposed by social norms, we make the set of choices $\{X\}$ known to an individual a union of all the consumption bundles previously chosen by their peers.[6] Thus, X_N is thus the subset of peers' choices that have been observed by or are otherwise known to the maximizing individual. We model X_N as only the known past choices made by peers because the maximizing individual may want an "empirical

[6]The set X_N does not include choices available to peers but not chosen by them because the maximizing individual only observes his/her peers actions. This set also does not include choices made by friends but not known to the maximizing individual. For instance, the participant who said that knowing women can be lawyers, doctors etc. empowered her did not say that knowing that women know they can be lawyers also empowered her. Therefore, we assume only the observed $\mathbf{x}^*$ matters. Although women with access to televisions may see women on cable shows being employed as lawyers, etc., actually meeting a woman engaged in professional employment is likely more salient and has a greater impact.

demonstration" (Montgomery and Casterline, 1996, p. 158) of the outcome of any given choice to gauge its feasibility. The more diverse a woman's network, the larger is X_N, and the more empowered her peers, the greater is her set of high-utility (to her) options in the choice set.

Second, we represent the effect of identity utility through networks by assuming the individual receives utility from belonging to a social network. This utility may be positive, if, say the individual is better off than her peers, and negative if she is worse than her peers. The additional bonus or penalty utility is denoted as U_N, and is a function of the average utility of the social network, N. We thus add identity utility U_N from the relative set or network N, to each utility function. Subscripts m and f denote male and female networks. Note also that identity utility increases in the strength of ties.

The third change to the basic Nash bargaining problem reflects social influence on individual bargaining power by making disagreement utilities V a function of networks because networks can provide support in domestic disputes and limit the potential for social sanction. The household thus faces the following maximization problem with respect to the constraints on $\mathbf{x}$ described above, and a full-income budget constraint.

$$\begin{aligned} \max_{\mathbf{x_{f,1}},\mathbf{x_{m,1}}} \quad & [U_f(\mathbf{x_{f,1}}) + EU_f(\mathbf{x_{f,2}}) + U_N(N_f, \mathbf{x}^*_{\mathbf{N_0,f}}) - V_f(N_{f,1})]^\alpha \\ & \cdot [U_m(\mathbf{x_{m,1}}) + EU_m(\mathbf{x_{m,2}}) + U_N(N_m, \mathbf{x}^*_{\mathbf{N_0,m}}) - V_m(N_{m,1})]^\beta \end{aligned} \tag{1}$$

$$\mathbf{x} \in \{X\} \tag{2}$$

$$X = f(X_{N_0}) \tag{3}$$

$$X_{N0} = \bigcup \mathbf{x}^*_{\mathbf{N_0}} \tag{4}$$

The household's full-income budget constraint (FIBC) derives from the individual budget constraints faced by the man and the woman. Each gets utility from consuming the vector of goods $\mathbf{x}$ in each time period. The vectors $\mathbf{p_m}$ and $\mathbf{p_f}$ reflect the prices faced by the man and the woman, including wages; the primary cost paid is for leisure, l. An individual pays for his or her consumption bundle from her income, which comes from wages and, in period 2, from transfers from children which are a function of the household investment, r, which is the numeraire good. Since women have a lower expected wage and a longer life expectancy, they have an economic incentive to invest more in their children. Hence, the woman's optimal choice of r is greater than the man's optimal choice. The woman's share of the household's resources, θ, is parametrically defined by α and β; these shares are given by norms and are not a bargaining outcome. The woman's FIBC looks as follows:

$$r_f + \mathbf{p_f}(\mathbf{x_{f,1}} + \mathbf{x_{f,2}}) \leq \theta(\alpha, \beta) \left[\sum_{t=1,2} Y_{f,t} + (Y_{m,1} + \rho Y_{m,2}) + E(T_f(r)) + \rho E(T_m(r)) \right] \tag{5}$$

where ρ represents the probability that the woman is married in period 2. $E(T)$ refers to the expected transfers from children. The man's FIBC looks as follows:

$$r_f + \mathbf{p_m}(\mathbf{x_{m,1}} + \mathbf{x_{m,2}}) \leq (1 - \theta(\alpha, \beta)) \left[\sum_{t=1,2} Y_{m,t} + (Y_{f,1} + \rho Y_{f,2}) + E(T_m(r)) + \rho E(T_f(r)) \right] \tag{6}$$

Adding up the constraints in equation 5 and equation 6 yields the full-income budget constraint faced by the household (equation 7).

$$\begin{aligned} (r_f + r_m) + \mathbf{p_f}(\mathbf{x_{f,1}} + \mathbf{x_{f,2}}) + \mathbf{p_m}(\mathbf{x_{m,1}} + \mathbf{x_{m,2}}) \leq \\ \sum_{t=1,2} Y_{m,t} + \theta(\alpha, \beta) \left[\sum_t Y_{f,t} - \sum_t Y_{m,t} \right] + \theta(\alpha, \beta)(Y_{m,1} + \rho Y_{m,2} - Y_{f,1} - \rho Y_{f,2}) \\ +(Y_{f,1} + \rho Y_{f,2}) + [E(T_m(r)) + \rho(E(T_f(r)) - \theta(\alpha, \beta)E(T_m(r)) - \theta(\alpha, \beta)\rho E(T_f(r)))] \end{aligned} \tag{7}$$

In this model, parents invest in children for consumption smoothing purposes. An increase in education, such as provided by *Mahila Samakhya*, raises bargaining power, and potential household and individual income, which have different effects on investments in children. Education raises investment in children only so far as higher bargaining power outweighs the countervailing effect of increased potential individual income. Education no longer increases investment in children once the increase in bargaining power is smaller than the increase in potential income. However, due to consumption smoothing, the increased differential in current versus future household income increases demand for future transfers, and thus investment in children. As long as women live longer than men and have lower average income, an increase in women's educational attainment will likely increase investment in children.

Consider the husband and wife's utility to be the outputs produced by the household; these outputs are a function of the utility from labor allocation, consumption, investment in children, and participation in networks. A household utility possibilities frontier (UPF) illustrates all the maximum feasible utility pairs for the husband and wife. Following the earlier discussion, the model yields three ways in which networks affect female empowerment: (1) Social Learning: Not knowing about all the choices or feasible levels of utility might constrain the equilibrium to a subset of the full UPF. Peer networks may facilitate learning about other possible outcomes. (2) Social influence: Social norms and peers may affect a woman's reservation utility. Further, levels of and changes in bargaining power can affect the observed equilibrium. If a woman does not have much bargaining power, the equilibrium will result in greater utility to the husband than to the wife. (3) Finally, if the woman's peers abide by norms, i.e. do not work and have little or no education, the household may be on a lower UPF than it would otherwise. Over time, as more women participate in *Mahila Samakhya*, norms might change to become more conducive to greater bargaining power for women. We detail each of these mechanisms below.

Social Learning

Participation expands peer networks and access to information. In interviews, women reported not even knowing five people outside their families prior to participation in the program. *Mahila Samakhya* introduces them to many more women, and through them, exposes them to information on the opportunities and facilities available to women. Social learning can help remove the constraints placed by norms so women have more choices. A woman can learn new information from her peers. She may not have realized certain choices were available to her (for instance, the ability to study or work). This effect can be thought of "as expanding the set of choices known to the woman" (Montgomery and Casterline, 1996, p. 158). Further, the outcomes of the educational and employment choices made by her friends provide an "empirical demonstration of the range of consequences that can follow from the adoption of a particular choice and may thereby shape the woman's subjective probability distributions" (Montgomery and Casterline, 1996, p. 158). Such learning is not restricted to close friends and can occur through "weak ties" (Granovetter, 1973), including ties with program participants from other villages.

Information about new opportunities can also be beneficial for women who cannot necessarily adopt those new opportunities themselves. The information of opportunities can be valuable for its own sake. For instance, one interviewed participant said that just knowing that women can be successful lawyers, officers, teachers, and entrepreneurs caused her to want to earn an income and be more self-reliant. This effect of information is consistent with the finding that urban Indian women with access to cable television were more empowered than those without cable television (Jensen and Oster, 2009).

Figure 2 illustrates how the constraints placed by limited information can restrict the UPF to a small portion of the true frontier. Point A is a possible equilibrium outcome, at which the husband's utility is U_A^m and the wife's utility is U_A^f. However, neither spouse knows the extent of the true UPF because social norms constrain the information about their choices to less than the full feasible set. Constraints on the husband restrict the frontier along the x-axis, while constraints on the wife limit the frontier along the y-axis. Point B is on the same UPF but is not available because point B is unknown to her. The indirect network effect of *Mahila Samakhya* removes the constraints— initially only for the woman, but eventually also for her husband. Point B now becomes feasible. A move to point B would increase her utility ($U_B^f > U_A^f$) and decrease her husband's utility ($U_B^m < U_A^m$). While this discussion treats the bargain as a zero-sum game, newly-expanded networks can in fact improve the entire household's utility by empowering the woman to earn an income and thus expanding the household UPF.

Social Influence

Strong networks provide support groups that influence individual behavior and may increase the woman's power within her household, or alternatively, reinforce restrictive social norms. Individuals learn from and are influenced by friends. Observing peers adopt new behaviors influences a woman's behavior because she trusts her peers and their judgement. Participants in *Mahila Samakhya* have more opportunities to interact with their peers, especially away from home. They develop a stronger network that can support them if they face domestic violence, or otherwise help change the household resource allocation. A woman with no support group may remain in the status quo for fear of being ostracized.

A critical mass of empowered, educated, and mobile women can change the village culture. Participants told us that before joining the program they faced a constricting social norm, reinforced by the village culture. They could not work, had little education, had limited say in the resources allocated to their children, and were encouraged to discriminate against daughters. Their identity was always subsumed in their husband's, brother's, father's, or in-laws' identity. After participating in *Mahila Samakhya* and interacting with other participants, women realize they have their own identity, that they can work if they want to, that they should study, and that they can influence household and community decisions. In the long run, as more people invest in their children, and investments become more equitable between the two sexes, the village culture will reflect the new patterns in investment.

By organizing women into support groups, the program can increase their power within the household and community without fear of social sanction. The support group also intervenes directly when a participant's family refuses to improve its treatment of her. In field tests, a participant reported that her *Mahila Samakhya* network intervened when her husband and in-laws did not allow her to feed her daughter as well as her son. Another respondent said that her husband's treatment of her improved after she joined *Mahila Samakhya* because he was worried that program officials would intervene in his domestic life and shame him in the village.

The question then arises, why do social norms that harm individuals persist in the absence of an intervention like *Mahila Samakhya*, and how do network-based learning and influence interact with such norms? Akerlof (1980) notes social norms disadvantageous to individuals may persist for fear of social sanction by the group against the individual trying to challenge the social norm, which is a form social influence. Further, people may not want to be outliers because of a negative feedback loop resulting from the social relativism of others. Program participants often reported being unsure what others would say if they tried to stand up to their in-laws or stop their husbands from hitting them: "we did not want to risk being different." By providing an in-built support group, the program helps women challenge this status quo.

Figure 3 represents the household's utility space, a UPF, and the equilibrium resulting from the husband and wife's choice sets. The dashed lines represent the husband and wife's levels of disagreement utility. If the bargain breaks down, they receive V_m and V_f, represented in utility-space by the intersection of the two dashed lines. The disagreement utilities place lower bounds on the UPF with respect to the $x-$ and $y-$ axes. Now consider the situation in which a woman near the disagreement utility joins *Mahila Samakhya*, and the resultant support group intervenes in her domestic situation and increases her disagreement utility so that she is better-off even if the bargain breaks down. Also consider the case in which her husband's disagreement utility decreases because the support group forces him to improve his treatment of her. The new disagreement utilities, represented by the dotted lines, expose a previously-unattainable part of the UPF that represents higher utility to the woman, and limits part of the UPF associated with lower utility to her.

The anecdote of the woman who said her husband's treatment of her improved after she joined the program because he was afraid of being shamed in the village illustrates this effect on bargaining power. By providing support groups the program decreases the woman's fear of ostracism and empowers her to change her situation within the household. Social influence thus enables the woman to change the available UPF to include better outcomes for her and restrict the possibilities that make her worse off. The educational effect of the program also increases the woman's disagreement utility because knowing about better job prospects and having more marketable skills raise her expected wages and thus increase her bargaining power. Note that the observed outcomes in the event of a breakdown in the bargain depend on social norms, as reflected by parameters α and β. Participation in *Mahila Samakhya* changes both the level of disagreement utility as well as α and β.

The household's relative value of a woman's happiness increases in the woman's bargaining power, hence the slope of the indifference curve at the point of tangency to the UPF is the ratio of bargaining powers, BP_f/BP_m. To observe an equilibrium where the woman gets a larger share of utility, the value of the exponent α must increase. The values of α and β depend on social norms. If the culture is such that women do not get a large share of utility, then α will continue to be low. By changing endogenous individual characteristics like education and mobility, *Mahila Samakhya* changes the norms. Over time, exposure to the program can result in a new culture where the exponents are similar in magnitude, reflecting a more equal distribution of bargaining power.

Identity Utility

In addition to strengthening ties with existing peers, *Mahila Samakhya* also diversifies networks (Kandpal and Baylis, 2013). By thus defining the frame against which people define themselves (Hoff and Pandey, 2014), the program shapes the identity of both participants and non-participants, particularly those non-participants that have participant friends. In particular, the program changes the participant's relative set of peers so that the people she compares herself with are now more educated and have less traditional attitudes about women's role in society. In initial interviews, respondents often talked of the pride they felt in being program participants, and how they were happier because of the changes in their peer network. Non-participants have weaker ties to peers, hence their identity utility from belonging to a network is lower than that of participants. Peers behave like one another not only to avoid conflict and to coordinate with each other but also because they gain identity utility from being insiders in the group (Akerlof and Kranton, 2010). Identity is endogenous and thus identity utility is influenced by changes in the reference group. Note that, identity utility is a mechanism of social influence, and as such, we are unable to empirically estimate it separately. However, the exposition below helps explain one of the key ways through which social influence may be expected to work.

The identity-related effect of networks might be to shift the UPF available to the household. The woman's utility is a function of the attitude or actions of her relative set of peers that she observed in the previous period. She defines her well-being relative to this set, and gains identity utility from behaving like the people in the set (Akerlof and Kranton, 2010). If these peers have traditional attitudes and adhere to the social norm although it discriminates against them, their ties are likely to be weak, hence the woman's gain in identity utility is also low. Such a relative set leaves little scope for social learning and may cause the woman's household to be on a lower UPF than they can attain. However, identity also has a relative component. The woman gains utility from being at least as well off as her peers, and loses utility if she is worse-off than them. By observing other women holding jobs and being educated, the woman is motivated to make similar changes in her life. If the program strengthens a woman's peer network, she stands to gain identity utility. The program also introduces her to more empowered women, who likely receive a greater share of the household's utility. She now needs a higher level of utility than before to be as well off as her peers. At point A in figure 4, without accounting for identity utility, the woman receives U_A^f in utility. However, her peers have some arbitrarily chosen higher level of utility, U_r^1, which effectively shifts back her UPF. After accounting for this loss in utility, the woman only receives $U_A^{f,r}$. The loss in utility from U_A^f to

$U_A^{f,r}$ represents the negative identity utility to the woman from being worse off than her peers.

If the equilibrium occurs at point B, the woman is better off than her peers, which is represented by a shifting out her of her UPF. The gain in identity utility means she effectively receives $U_B^{f,r}$, which is greater than U_B^f. Now if the woman's relative set changes because of *Mahila Samakhya* and the new relative set has higher utility, U_r^2, the woman needs a greater gain in utility to be as well-off as before. Some parts of the UPF (between X and Y on the $y-$axis, where she was better-off than a less empowered relative set) shift in because she is worse off than her new relative set. Stronger networks from participation thus lead to a greater change in identity utility than a weaker network.

In this framework, the peer effect of the program thus works through networks to change the woman's bargaining power, increase the feasible set of choices available to her, and change the UPF that is attainable to her household.

4 Data

Household data from India do not include information on self-reported networks, and preclude an analysis of the effect of networks on child welfare. Researchers have used caste to proxy for peers in India because caste is a strong signifier of networks (Munshi and Rosenzweig, 2006), but there may be networks of varying strength within castes. As a result, we collect data from the north Indian state of Uttarakhand on women's peer networks, instruments for social learning, influence, female power, and their role on child nutrition outcomes. In addition, we also collect data on participation in *Mahila Samakhya*. Program centers have been present in Uttarakhand villages for periods lasting anywhere from three months to five years, allowing us to use time-variation in exposure to the program to identify its impact on networks and child nutrition.

Our data are from six of thirteen districts in Uttarakhand, four with the program and two without (the state of Uttarakhand is represented by the cross-hatched region in Figure 1). The survey districts are represented in the inset of Figure 1 with a dotted pattern. The four dotted districts with a thick border are surveyed program districts. The two dotted districts without a thick border are surveyed non-program districts. Villages within the sample were randomly chosen. We designed the survey to trace self-reported networks, and implemented restricted snowball sampling.

In each village, we interviewed a randomly chosen woman and asked her to list five people outside her household[7] with whom she was in contact on a regular (daily or weekly) basis. We then conducted follow-up interviews with two randomly-selected women from these five friends. We asked each of these two follow-up interviewees about five of their closest friends, and interviewed two friends each. Thus, starting with one

[7]The question did not specify the gender of these five people; nonetheless, respondents only listed women.

woman, the sampling strategy yielded a network of seven. The final sample is of 487 women belong to 72 networks across 69 villages; thirteen networks spanned more than one village. In seven cases, friends of friends listed the first woman as a friend; the analysis below drops these seven cases. Chandrasekhar and Lewis (2011) estimate large, albeit downward, biases, of up to 90 percent, when using random draws or top coding to sample peer networks. When field testing the questionnaire, over 95 percent participants reported regularly communicating with fewer than five people outside their families, particularly prior to program participation. As a result, five appeared to be an effective upper limit on network size in our sample. Indeed, only 42 of our sample of 487 women reported five friends.[8]

As Table 1 shows, the average woman in our sample is 32 years old, while her husband is 38 years old. She married at age 19 and has 9 years of education, while her husband has an additional year of education. The average age of her sons is 8, and that of her daughters is 6. The average woman's house has three rooms and electricity. Table 3 tells us that 78.17 percent of the program participants but only 58.82 percent of non-participants could leave the house without permission. Similarly, while 68.02 percent of participants have NREGS identification cards, only 48.94 percent of non-participants do. Table 4 shows that participants' children also consume more rice and lentils than non-participants children.

Kandpal et al. (2013) find evidence that participants select into *Mahila Samakhya*, but not that the program is targeted by geographic area in any meaningful way. Poorer participants neither select into the program nor are they targeted based on indicators of wealth (number of rooms, electrification, access to improved toilet facilities, and nature of the construction materials used for the floor and walls of the house).

5 Identification Strategy

The empirical analysis occurs in two steps: first, we identify causal peer effects. We instrument for the endogeneity of program participation using exposure to the program, and for the endogeneity of networks using instruments that capture the likelihood of contact: the number of other women in the village with a similar time to collect water and the number of other women in the village of the same caste. Second, we study the mechanisms through which the peer effects work. Note that peer effects can work directly on participants themselves, and also indirectly through the friends of participants. Further, the changes in reference group brought about by the program is essentially a peer effect.

[8]One concern we had during the survey was that when respondents observed that we would ask several questions about each friend, they would only list a one or two friends instead of the true number. To avoid such bias, at the start of the interview, we simply asked respondents to list the names of their friends and asked detailed questions about these friends further on in the survey.

5.1 Endogeneity of Program Participation

We instrument for participation in *Mahila Samakhya* using the number of years a participant has lived in a village with *Mahila Samakhya* as an adult (defined here as older than 16), while separately controlling for age and village. We use the threshold of 16 for adulthood because program participants can be no younger than 16 years of age. This variable thus tells us the potential years of exposure of an adult to the program, and is correlated with participation. Further, any effect of this variable on female empowerment likely works through participation in the program, rather than directly and the variable is driven by the year the program started as there is little migration among married women in the region. However, because women often migrate at the time of marriage, their exposure to the program might have started in their natal village through a participant friend or parent. Since we do not know whether the woman's natal village had the program, exogamous matrimony might lead to measurement error, which in turn would bias results downwards, particularly in the first stage. Such downward bias might induce a weak instruments problem, but, as we demonstrate below, our instruments do not appear to be weak. Nonetheless, given that unmarried women do not participate in the program, exposure would have had to be indirect, and thus the resultant bias would likely be small.

5.2 Identifying Peer Effects

With observational data on outcomes y of an individual i and attributes x, a researcher seeking to understand the impact of $i's$ social network may wish to estimate the following model (Manski, 1993):

$$E(y_i|x_i) = \alpha + \beta\bar{y} + \gamma\bar{x} + \delta x_i + \epsilon_i \tag{8}$$

where $\bar{y}$ is the of average outcome in the network and $\bar{x}$ represents the network average of attribute x. In a model linear in x and y, it is impossible to identify β and γ because $\bar{y}$ also depends on $\bar{x}$. In this context, Manski (1993) presents three hypotheses that may explain the observed similarities in the behavior of friends. (1) Correlated effects occur when people act alike because they face a similar environment or have similar characteristics. (2) Contextual effects describe the fact that individuals are more likely to act in a given way depending on the distribution of group members' characteristics. (3) Endogenous effects represent the phenomenon where the group affects individual behavior through social interaction. The third effect is key to identifying the causal network effect, but may still be confounded by the reflection problem, i.e. does i influence the group's behavior or does the group influence i?

Much of the literature following Manski has focused on the econometric issue of separating the causal peer effect from that of correlated unobservables (Conley and Udry, 2010; Miguel and Kremer, 2004; Foster and

Rosenzweig, 1995; Bandiera and Rasul, 2006). Two ways of disentangling these effects are to (1) randomize the networks (Sacerdote, 2001; Zimmerman, 2003; Duflo and Saez, 2003) or (2) randomize an intervention or new technology at the friend-level (Banerjee et al., 2012; Oster and Thornton, 2012; Godlonton and Thornton, 2012; Kremer and Miguel, 2007). However, since neither networks nor information flows are exogenously determined in practice, the policy implications of such approaches are unclear. Our identification strategy uses instrumental variables with a spatial weighting technique (Kelejian and Prucha, 1998) to identify causal peer effects in the context of endogenously-formed networks and information flows. The Kelejian and Prucha (1998) estimator can be written as follows:

$$Y = \alpha + \gamma WY(WWX) + \epsilon \tag{9}$$

Y is a vector of outcomes, X is a vector of characteristics, W is a row-normalized 0/1 matrix of friends. The identifying assumption is that a spatial unit is only influenced by neighbors of its neighbors through the mutual neighbor. Recent extensions of spatial econometrics to networks have relied on the Generalized Spatial 2SLS estimator by using partially overlapping networks (Lee, 2007; Bramoullé et al., 2009; de Giorgi et al., 2010). The exclusion restriction here is that friends of friends[9] only affect behavior through the mutual friend. Given data on pre-existing networks, this extension of the GS2SLS estimator thus relies on two key assumptions: the first is that this exclusion restriction holds and the second is that group formation is separable from information flows. A limitation of our data (and most available datasets, including those used earlier) is that we do not know entire networks, simply five of the woman's friends. Since the top code of five does not appear to be restrictive, the exclusion restriction is likely to hold. Further, we use instruments identified during fieldwork to account for endogenous group formation, which crucially allows us to relax the assumption of separability of group formation and information flows. In effect, then, while the original GS2SLS is a Generalized Least Squares estimator, in this paper, we instrument for both the weights matrix W and the explanatory variables X. Our regression equation can be written as follows:

$$Y = \alpha + \beta X(Z) + \gamma WX(WWX(VVZ)) + \epsilon \tag{10}$$

where V is the instrumented network of friends and Z is the vector of instruments for participation. Our instrument for group formation is the number of women of the same caste in the village. We treat women of the same caste within a village as potential friends in keeping with the literature from India showing that caste networks determine social ties (Hoff and Pandey, 2006; Munshi and Rosenzweig, 2006), particularly of

[9] Friends of friends are individuals who are in your reported friend's network, but neither you nor the friend-of-the-friend listed the other as a friend.

women (Dyson and Moore, 1983).[10] We then generate two network weights matrices: one which identifies all self-reported friends, and a second that identifies all potential friends using caste as a proxy. To generate instruments for the true weighted participation of friends, we multiply the caste weights matrix with the exposure to the program vector. These network-weighted instruments thus reflect the average number of years all potential friends have lived, as adults, in a village with the program.

Even after identifying the causal effect, the reflection problem remains to be accounted for. While Lee (2007); Bramoullé et al. (2009); de Giorgi et al. (2010) assume that social networks are directed[11], we attempt to relax this assumption by estimating the marginal effect of friends' participation on non-participants. The identifying assumption is thus that, given existing social norms governing household decision making, the *Mahila Samakhya* program only affects a non-participant's household bargaining power and her children's food consumption through her participant friends. Thus, our estimates of the effect of friends' participation on non-participants is likely not contaminated by the reflection problem. Correlated effects remain a source of bias in such analysis, particularly in the presence of proxy-reported peer behavior (Hogset and Barrett, 2010). Since we conduct follow-up interviews with friends and use these primary data, our data do not have measurement error from proxy reports. The standard errors reported below are also clustered at the network level, further reducing contamination from correlated effects at the network level.

6 Estimates of the Causal Peer Effect

We use three dependent variables for the woman's bargaining power: (1) whether the woman works outside the household, (2) whether her name is on her household's NREGS identification card, and (3) whether she is able to leave the house without permission to go to the market for routine purchases. In these estimations, we include controls for (1) the woman's pre-determined personal characteristics, namely age, spousal age difference, years of education and a binary variable for less than four years of education, which is a modal point in the data; (2) household demographic characteristics: the number and average age of the woman's children, whether the household is Brahmin, and whether the parents in-law live in the household, and (3) a household-level wealth index (Filmer and Pritchett, 2001). We first estimate the peer effects on these three bargaining power outcomes as linear probability models without instrumenting for endogenous program participation or network formation. Results presented in Table 5 show that as the number of friends who participate in *Mahila Samakhya* increases from zero to 3.62, the probability of a non-participant working

[10] Kandpal and Baylis (2013) show that the *Mahila Samakhya* program also serves to diversify peer networks, and that participants tend to have significantly more friends from other castes than do non-participants. Therefore, by using caste to instrument for self-reported friends, we may underestimate the effect of the program; nonetheless, we are able to report significant peer effects.

[11] The directionality assumption implies that the individual listing friends is the one being influenced by her peers, while the peers are not equally influenced by the individual listing them.

outside the household increases by four percentage points. Results also suggest that friends' participation increases the probability of both non-participants and participants being able to leave the house without permission, although the former effect is not statistically different from zero. Last, we note that all three outcomes are positively related to own participation.

In addition to the three woman-level dependent variables, we use household fixed effects to consider the effect of the mother's friends' participation in *Mahila Samakhya* on the food consumed by her children aged 21 and younger. Table 6 presents the results for the household fixed effects regression of children's rice and lentil consumption without instrumenting for the mother's friends or participation in *Mahila Samakhya*. Results show that going from zero to 3.62 participant friends decreases by 0.066 bowls the amount of rice consumed by daughters while increasing by 0.067 bowls the amount of lentils consumed by girls, although the latter effect is not statistically significant. The similar magnitudes of these estimates may suggest a switch to a more nutrient-rich diet for daughters of non-participants who have friends who participate in *Mahila Samakhya*. However, we do not treat the results presented in Tables 5 and 6 as causal since participants and non-participants may be different over unobservables that likely also affect bargaining power outcomes including the three presented here.

To address this potential endogeneity of participation and network formation, we use the instruments described in the previous section: exposure to the program and the number of women, also weighted by program exposure, of the same caste. First, we test the validity of the instruments by first regressing the two endogenous participation variables, own participation and weighted friends' participation against their respective instruments: exposure to the program and exposure to the program of women in the same caste in the village. Results presented in Table 7 show that both instruments are significant and positively correlated with participation in the program for the first two dependent variables. The instrument for networks has an F-statistic of 28.43, suggesting that it is strong; the instrument for own participation has an F-statistic of 8.35, which is just below the Stock-Staiger rule of thumb of 10. However, the instrument appears to be a good predictor of participation: a one standard deviation increase in the instrument for own participation yields a 0.37 standard deviation increase in the probability of participation; a one standard deviation increase in the instrument for networks results in a 0.39 standard deviation increase in friends' participation.

Causal peer effects on household bargaining outcomes, using instrumented probit regressions, are outlined in Table 8. The corresponding marginal effects are presented Table 9. These results tell us whether own and friends' participation in *Mahila Samakhya* increase the three individual-level measures of the woman's bargaining power: working outside the family farm, having her name on the NREGS card, and her ability to leave the house without permission. Of particular note is the effect of friends' participation on non-participants Table 9, since this is the estimate requiring the weakest directionality assumption. In other words, for this marginal effect, the identifying assumption is simply that the *Mahila Samakhya* program affects a non-participant's household bargaining power through her participant friends. The effect indeed appears to be driving the significant effects of friends' participation on female mobility and employment outcomes. An increase from zero to 3.6 participant friends increases a non-participant's probability of, both, working outside of the home and leaving the house without permission. These effects are relatively large: 15.7 percentage points for the probability of working outside the household, and 18.2 percentage points on being able to leave the household without permission. On the other hand, an increase in friends' participation significantly decreases the likelihood of a non-participant having her name on her household's NREGS card. Supplementary qualitative work suggests that this result may be driven by the difficulty in obtaining a card, which is explicitly recognized by participants when they describe the back and forth with the local NREGS supervisor and stress the importance of having approached the supervisor as a group. This information may be discouraging to non-participants who often do not have a critical mass of friends with whom to approach NREGS officials. In contrast, we observe almost no effect of friends' participation on *Mahila Samakhya* participants for any of these three outcomes, implying that the additional effect of having friends participate does not add or detract from the primary effect of participating oneself.

Finally, using instruments for participation and networks, and household fixed effects, we examine the allocation of food within households. Results presented in Table 10 show, overall, children whose mothers have friends who participate in *Mahila Samakhya* tend to eat more rice and lentils. However, girls consume 0.87 fewer bowls of lentils, per day, than boys. On the other hand, daughters of *Mahila Samakhya* participants consume about 0.89 bowls more than the average girl, relative to boys in the same household, although this effect is not precisely estimated. Thus, while participation does not eliminate the discrepancy between boys and girls' food consumption, it appears to reduce the gap. Crucially, the marginal effects, presented in Table 11, show that daughters of non-participant mothers with participant friends consume 0.227 additional bowls of lentils. In line with the literature suggesting that more empowered women invest more equally in children of both sexes than do less empowered women, this result is strongly suggestive of peer effects existing in the household bargain.

7 Heterogeneity Analysis: Decomposing the Mechanisms

Next, we attempt to disentangle social learning from social influence. We describe the proxies for social learning and influence below; while we cannot rule out that the proxies for either mechanism might be contaminated by observables or unobservables correlated with one of the other mechanisms, we argue below that these proxies primarily pick up the mechanism they are intended to measure, and find that our results are robust to using alternative proxies.

Social Learning

Intuitively, any constraints on the household PPF are more binding on women who do not have much access to information before the program. Thus, we hypothesize that women with low education are less exposed to information and thus have more to gain through social learning, and measure social learning using an interaction between low education, and friends' participation in *Mahila Samakhya*. We define low education as four or fewer years of education because it is the modal point: 72.24 percent of the woman in our sample had at least five years of education. We expect the interactions of low education with own and friends' participation to have positive effects on female bargaining power and children's food consumption, while low education by itself may have a negative effect on the outcomes.

Social Influence

Influence in the form of changes to disagreement utility most affects women whose agreement utility is close to their disagreement utility, i.e. those with low initial bargaining power. Women who have low initial bargaining power, but now themselves participate, or have friends who participate, in *Mahila Samakhya* may gain more from social influence than those with higher initial bargaining power. However, since bargaining power itself is an outcome of program participation, we need a measure of bargaining power that is unchanged by participation. We proxy for initial bargaining power using the spouses' age difference because only married women participate in *Mahila Samakhya*. Note that while having a mother (or mother-in-law) who participated in *Mahila Samakhya* may affect the spousal age difference, the program only entered the surveyed villages between 2004 and 2008 and the average respondent is 32 years old, making it unlikely that women would have had a mother or future mother-in-law participate before they were married.

As presented in Table 12, we see little evidence of social learning in individual-level female empowerment measures. The effect of friends' participation on the probability of working outside the household and not needing permission to leave the house is muted for women with low education. Specifically, the effect of friend's participation on the probability of working outside the household and being able to leave the house without permission is approximately half that for women with low education compared to women with more than four years of schooling. The only effect that is greater for low education women is the negative effect on friends' participation on having an NREGS card, which is consistent with our hypothesis of higher barriers to entry into NREGS for non-participants and women with low bargaining power.

Conversely, as shown in Table 13, we find evidence suggestive of social influence in the household bargain. All effects of friends' participation are larger for those women with lower initial bargaining power as measured by the spousal age difference. As above, this effect is primarily driven by the effect on non-participants, for whom we observe that the effect having going from zero to 3.62 participant friends increases the probability of being able to leave the house without permission by 3.6 percentage points, while also increasing the probability of working outside the household, albeit not significantly, to the tune of 2.9 percentage points. Thus, it appears that the effect of friends' participation on bargaining power largely works through social influence, and is more effective for women who already have some initial bargaining power and access to information.

Table 14 presents evidence on the mechanisms underlying the effect for friends' participation on the amount of lentils consumed by girls. The higher lentil consumption by daughters of non-participants with participant friends appears to be driven by women with low education, which suggests that social learning is the underlying mechanism for peer effects on children's food consumption. Note that women with greater spousal age differences are less influenced by their friends' participation, suggesting again that non-participants may need a minimum level of initial bargaining power to make use of the information, although this effect is not precisely estimated.

7.1 Sensitivity Analyses

Falsification test

Our results suggest the presence of a causal peer effect based on our snowball sampling-driven identification strategy. However, what if these estimates were simply picking up other patterns in the data and not actual networks? We conducted 500 iterations of a falsification test by randomly assigning each woman in our sample to a network of six other "friends" and "friends of friends" and re-estimating the peer effects. In over 473 of the 500 iterations, we find no statistically significant peer interactions among women that have been assigned randomly to a peer network which strongly suggests that the results reported in this paper are the result of causal peer effects and not non-observables in the data.

Program Placement

In addition to network formation and the program participation decision, endogeneity could arise if *Mahila Samakhya* were systematically placed in villages where women have a relatively high level of bargaining power and thus are more likely to respond favorably to the treatment. We use data from the Indian censuses of 1991 and 2001 on village-level female bargaining power. Matching the year that *Mahila Samakhya* entered the smallest administrative cluster of villages (block) to the most recent census before that year, we compare the levels of bargaining power clusters that received *Mahila Samakhya* with those that did not. Results for t-tests of equality, presented in Table 15, show no significant differences in sex ratio, the sex ratios for scheduled castes or tribes, and the literacy ratio. Similarly, the sex composition of the labor force also does not vary between treated and untreated cluster. It may further be that untreated districts do not represent statewide trends and that women in these districts are less (or more) empowered than average, implying that program placement may be targeted. However, the nationally-representative NFHS-3 (IIPS and ORC Macro, 2007) and DLHS-3 (Ministry of Health and Family Welfare and International Institute for Population Studies, 2010) show that the women in untreated districts in our sample do not differ significantly from the rest of the state. For instance, the average age at marriage for Uttarkhandi women is 20.6, while it is 19.09 in our untreated sample, and 19.38 in our treated sample; 43 percent of all Uttarkhandi women work while 49.81 percent of the untreated women in our sample do, and 50.66 percent of those in our treated sample do. The total fertility rate in the state is 2.6, which corresponds closely to the average family size of one boy and one girl in our untreated sample. Finally, while 84 percent of the state has access to electricity, 90 percent of our untreated sample does. Thus, these comparisons indicate that the program was not systematically targeted in any observable way.

Alternative Specifications

Qualitative interviews revealed that program participants tend to have slightly older sons, and a longer time to collect firewood. Hence, we tested sons' age[12] and time to collect fuel as alternative instruments. Parents in-law and the husband can perceive leaving a young son at home as neglecting one's duties, so women with young children are often unable to leave the house for extended periods of time, such as to attend program meetings. On the other hand, women who spend more time in the forest collecting firewood may feel more isolated and may be more interested in the community-building activities of the program. The instrument probit results using age of sons and time to collect firewood as instruments were similar to the ones presented above. However, we choose to highlight the results using the exposure instrument described above because it relies on program rules, and likely better meets the exclusion restriction.

Since a significantly greater proportion of program participants are Brahmin, it may be that being Brahmin affects both peer effects and program participation. We thus tried several specifications that included interaction terms of the Brahmin caste dummy with other right hand side variables. While these interaction terms improved the Akaike Information Criterion (AIC), the coefficient on the interaction terms were never significantly different from zero. As a result, the specification we report below does not include the interaction terms.

[12]For women with no sons, we set the age of sons to zero and separately controlled for number of sons in all regressions.

8 Conclusion

This paper examines peer effects in intrahousehold decision making. We use a community-level women's empowerment program, *Mahila Samakhya*, to identify shocks to female bargaining power. Using network-weighted instrumental variables in probit regressions, results show that women who do not participate in *Mahila Samakhya* but have friends who do, are less likely to need permission to leave the house and have a greater likelihood of working off the family farm. Using household fixed effects, we also find that the daughters of non-participants with participants friends tend to eat a more protein-rich diet than the daughters of non-participants with no participant friends. These estimates of causal peer effects relax two restrictive assumptions often made in the literature: (1) that of the separability group formation and information flows by instrumenting for networks, and (2) that of directionality of network ties by examining the impact of friends' participation on non-participants' bargaining power. We further hypothesize that peer effects in household decision-making work through the potential channels of information and influence. We then provide suggestive evidence that information and influence have different effects on the woman-level measures of bargaining power, namely physical mobility and working outside the household, than they do on children's food consumption, a household-level measure of bargaining power.

These results highlight the importance of peer networks, and suggest that female empowerment and child nutrition interventions may benefit from accounting for social learning and influence. Programs that harness social networks may be more effective at removing cultural barriers, including restrictive social norms, to development goals. Further, programs that take into account the peer effect may benefit from differentiating between the different mechanisms through which peer networks work. For example, programs that rely on social learning, i.e. ones that target lower educated women through their weak ties could just target a small number of well-placed women in a village. Such programs might include interventions aimed at increasing female labor force participation or improving children's food consumption or health outcomes. On the other hand, programs that rely on social influence or identity utility, such as interventions aimed at improving female mobility or physical independence may target clusters of villages to build up critical mass.

This analysis is, of course, not without caveats. The paper would benefit from panel data tracking women and their peer networks. Ideally, we would have been able to randomize a component of the *Mahila Samakhya* program, such as a literacy camp or support group participation, at the friend level, and follow its effect on individuals across time. Further, the limited snowball sampling strategy employed in data collection means that the results are not representative of the average Indian woman, or even the average Uttarakhandi. Generalizations of these results should therefore involve caution. Most importantly, we are unable to extrapolate past bargaining power and child food consumption to welfare in general. In particular, there are unclear impacts on the extensive margin if, for instance, girls receive more food but are made to spend less time on homework and more on household chores. Policy implications from this analysis must therefore involve caution since we only consider one part of a much larger picture.

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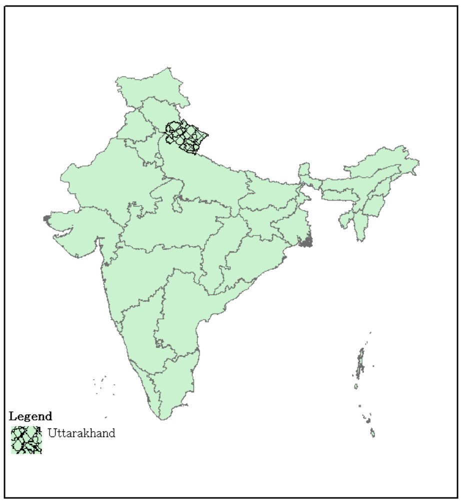
9 Figures and Tables

Figure 1: Uttarakhand



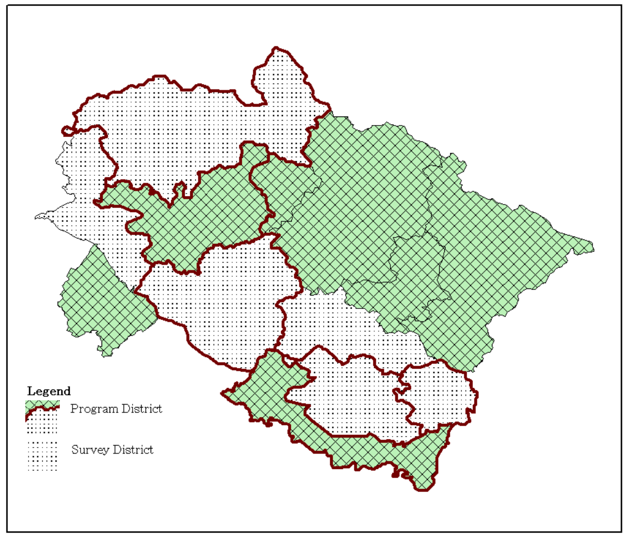


Table 1: Summary Statistics Using a Women's Empowerment Study, Uttarakhand, India, 2009-2010

Variables	Mean	Std. Dev	Min	Max	Observations
Respondent's Age	32.13	8.11	20	65	447
Husband's Age	37.76	9.25	23	80	414
Wife's Age-Husband's Age	-5.56	3.90	-29	5	414
Less than Four Years of Education	0.23	0.42	0	1	459
Respondent's Years of Education	7.56	4.93	0	17	459
Average Age of Sons	7.90	7.67	0	36	487
Average Age of Daughters	6.22	6.69	0	30	487
Number of Sons	1.22	0.89	0	5	487
Number of Daughters	1.07	1.02	0	5	487
Brahmin	0.19	0.39	0	1	487
Asset Index† Quintiles	2.99	1.42	1	5	404

† Filmer & Pritchett [2001].

Figure 2: Inefficiencies Can Constrain and Lower the Household Production Possibilities Frontier

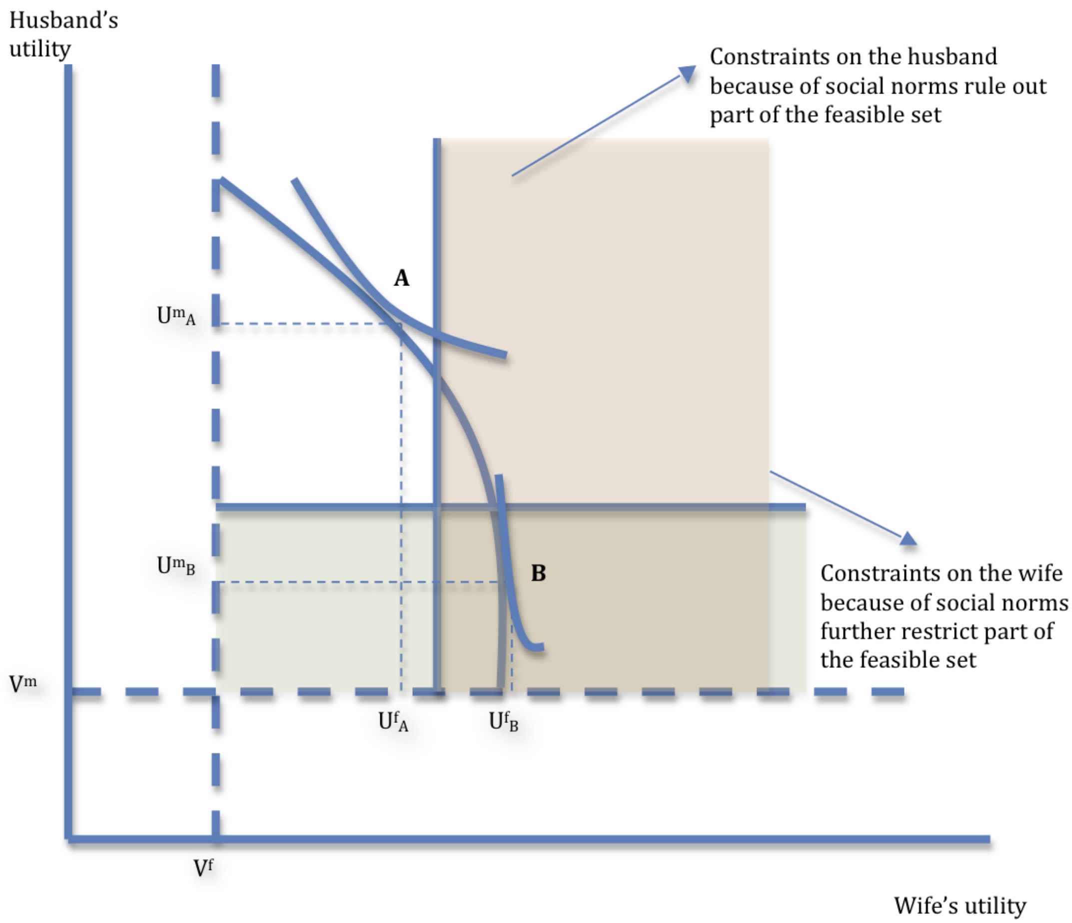


Table 2: Balance Between *Mahila Samakhya* Participants and Non-Participants

Variables	Non-participants	Participants	Difference	t-test	Observations
Age	30.67	33.06	-2.40	-2.61	447
Husband's Age	37.00	38.22	-1.21	-1.08	414
Spousal Age Difference	-6.02	-5.28	-0.74	-2.03	414
Less than Primary Educ.	0.19	0.26	-0.07	-1.48	459
Respondent's Years of Education	8.12	7.19	0.94	1.38	459
Average Age of Sons	7.26	8.97	-1.71	-1.81	487
Average Age of Daughters	6.33	6.54	-0.21	-0.25	487
Number of Sons	1.16	1.37	-0.21	-1.76	487
Number of Daughters	0.98	1.14	-0.16	-1.31	487
Brahmin	0.05	0.21	-0.16	-3.16	487
Asset Index† Quintiles	3.15	2.89	0.27	1.42	404

† Filmer & Pritchett [2001].

Figure 3: Inefficiencies Can Constrain and Lower the Household Production Possibilities Frontier

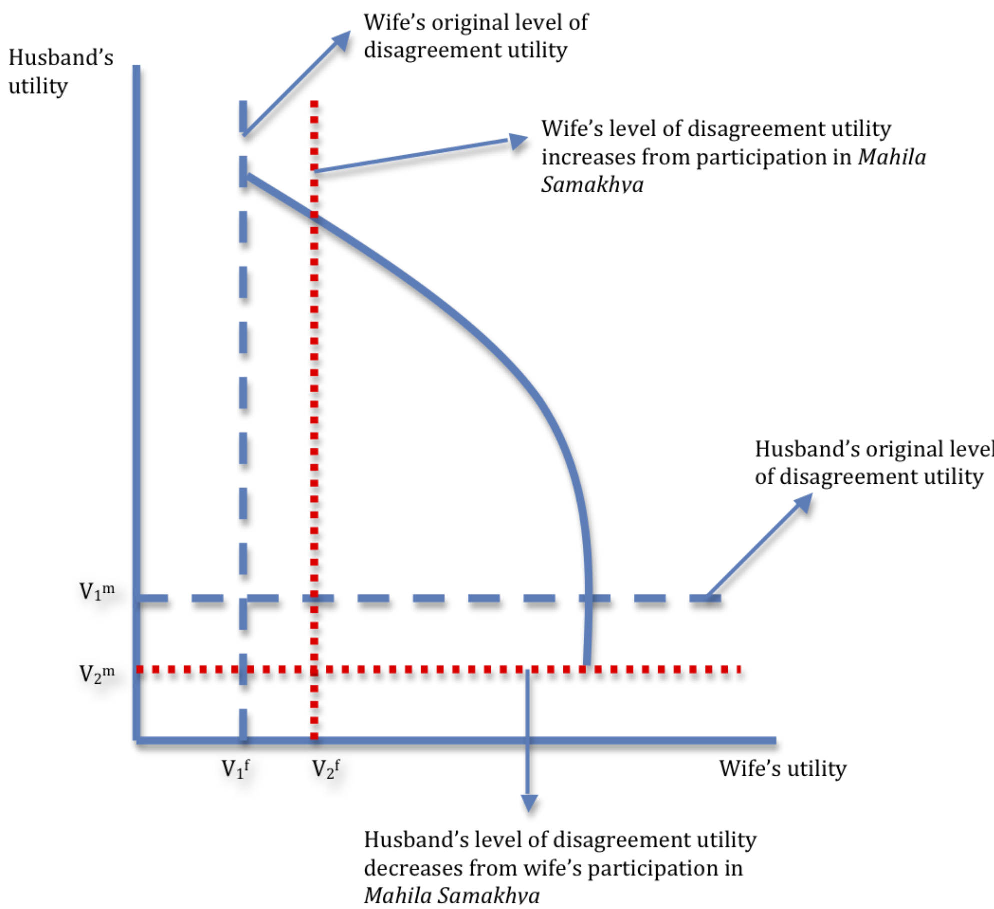


Figure 4: Inefficiencies Can Constrain and Lower the Household Production Possibilities Frontier

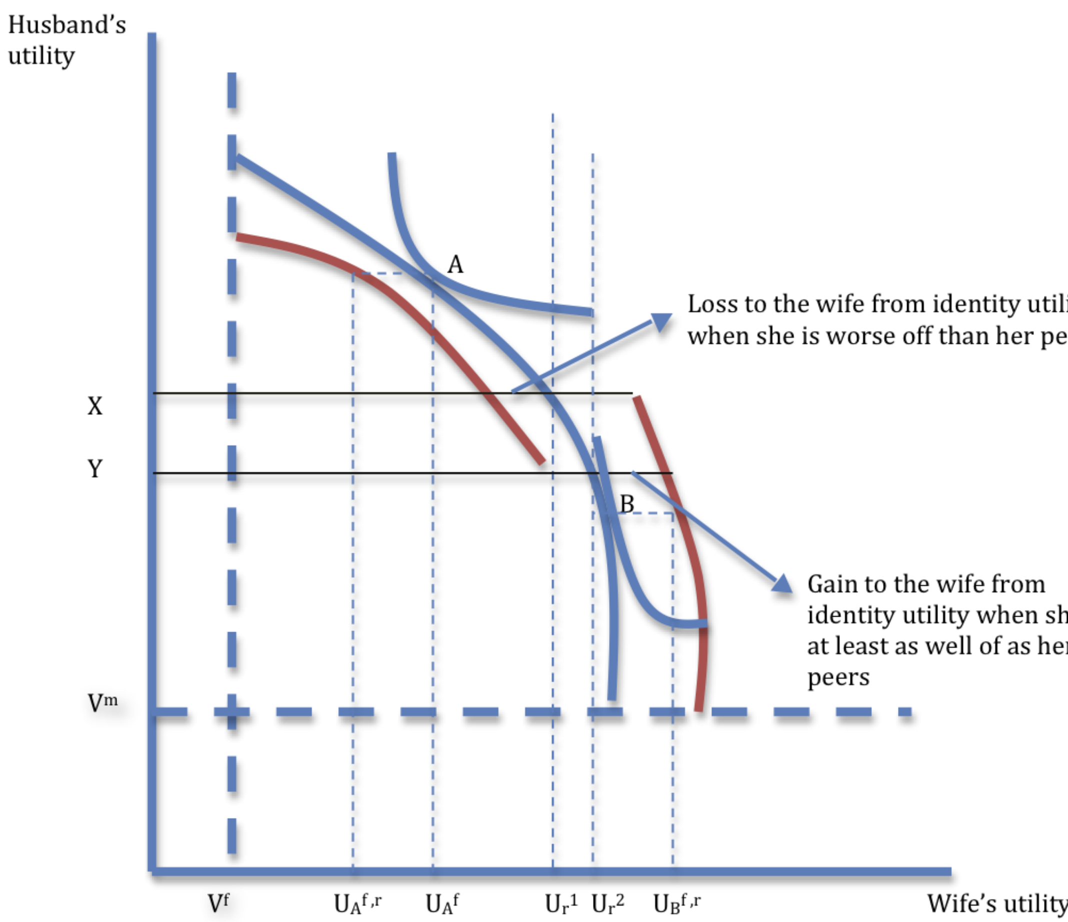


Table 3: Female Bargaining Power: Dependent Variables from a Women's Empowerment Study, Uttarakhand, India, 2009-2010

	Works Outside Household	Has Name on NREGS Card	Doesn't Need Permission
Non-participants	0.52	0.50	0.49
Participants	0.75	0.68	0.83
Difference	0.24	0.18	0.34
t-stat	5.02	3.66	7.69
Observations	404	404	404

Table 4: Standardized Bowls of Food Consumed by Children Younger than 21 in the Past 24 Hours: Dependent Variables Using a Women's Empowerment Study, Uttarakhand, India, 2009-2010

	Rice	Lentils
Non-participants	2.43	2.12
Participants	2.35	2.32
Difference	-0.08	-0.19
t-stat	0.59	-1.78
Observations	594	595

Table 5: OLS Regressions: Female Bargaining Power

	Works Outside Household	Has Name on NREGS Card	Doesn't Need Permission
Friends' Participation	0.040***	−0.011	0.015
	(0.010)	(0.008)	(0.010)
Friends' Participation*Own Participation	0.005	0.006	0.025*
	(0.013)	(0.013)	(0.015)
Own Participation	0.052	0.201**	0.172*
	(0.096)	(0.091)	(0.088)
Less than Four Years of Education	0.238***	0.028	0.014
	(0.079)	(0.089)	(0.079)
Spouse Age Difference	0.012**	0.005	−0.002
	(0.006)	(0.006)	(0.005)
Own Age	0.008*	0.002	0.003
	(0.004)	(0.004)	(0.003)
Years of Education	0.016**	0.000	−0.000
	(0.008)	(0.009)	(0.008)
Number of Children	−0.012	0.005	−0.034
	(0.023)	(0.026)	(0.021)
Age of Children	0.013***	0.012**	0.006
	(0.005)	(0.006)	(0.005)
Lives with In-laws	0.061	0.061	−0.055
	(0.053)	(0.059)	(0.048)
Brahmin	−0.003	−0.267***	−0.057
	(0.067)	(0.088)	(0.064)
Asset Index	−0.055*	−0.078*	0.002
	(0.033)	(0.040)	(0.033)
Constant	0.138	0.537***	0.438***
	(0.211)	(0.184)	(0.163)
Observations	404	404	404

Standard errors, clustered by network, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Gender Differences in Standardized Bowls of Food Consumed by Children Younger than 21 in the Past 24 Hours: Household Fixed Effects Without Instruments for Participation and Networks

	Rice	Lentils
Friends' Participation*Female Child	-0.066^{*}	0.067
	(0.034)	(0.065)
Friends' Participation*Own Participation*Female Child	0.070^{*}	-0.050
	(0.038)	(0.069)
Own Participation*Female Child	-0.191	-0.143
	(0.263)	(0.289)
Female Child	0.109	0.042
	(0.218)	(0.182)
Child Age	-0.000	-0.005
	(0.012)	(0.014)
Constant	2.367^{***}	2.286^{***}
	(0.139)	(0.135)
Observations	594	595

Standard errors, clustered by network, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This sample consists of 295 boys and 300 girls under the age of 21.

Table 7: Female Bargaining Power: Instrumenting for Endogenous Variables

	Own Participation	Friends' Participation
LN(Exposure to Program)	0.086***	
	(0.024)	
Same Caste*Exposure to Program		0.024***
		(0.006)
Less than 4 Years of Education	0.014	0.566
	(0.096)	(0.633)
Spousal Age Difference	0.010*	-0.026
	(0.005)	(0.032)
Own Age	-0.001	0.004
	(0.004)	(0.026)
Years of Education	-0.004	0.008
	(0.010)	(0.052)
Number of Children	0.030	0.373**
	(0.018)	(0.178)
Age of Children	-0.003	-0.009
	(0.004)	(0.040)
Lives with In-laws	-0.120**	-0.879*
	(0.052)	(0.495)
Brahmin	0.282***	1.562**
	(0.081)	(0.675)
Asset Index	-0.023	-0.027
	(0.039)	(0.252)
Constant	0.470**	1.178
	(0.209)	(1.089)
Observations	404	404
F-stat	8.35	28.43

Standard errors, clustered by network, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Female Bargaining Power: IV Probit Second-stage Regressions

	Works Outside Household	Has Name on NREGS Card	Doesn't Need Permission
Friends' Participation	0.586***	-0.632***	0.648***
	(0.140)	(0.157)	(0.154)
Friends' Participation*Own Participation	-0.386	0.564***	-0.561***
	(0.276)	(0.115)	(0.104)
Own Participation	0.366	0.010	0.625
	(0.580)	(0.741)	(0.608)
Less than Four Years of Education	0.174	0.226	-0.199
	(0.571)	(0.189)	(0.221)
Spousal Age Difference	0.050**	-0.039**	0.037**
	(0.022)	(0.017)	(0.015)
Own Age	0.019	-0.011	0.012
	(0.012)	(0.008)	(0.008)
Years of Education	0.003	0.025	-0.024
	(0.046)	(0.017)	(0.021)
Number of Children	0.033	-0.077*	0.031
	(0.069)	(0.040)	(0.067)
Age of Children	0.002	0.028**	-0.016
	(0.037)	(0.014)	(0.014)
Lives with In-laws	0.164	-0.020	0.031
	(0.184)	(0.161)	(0.148)
Brahmin	-0.096	-0.159	-0.102
	(0.348)	(0.230)	(0.358)
Asset Index	-0.091	0.034	-0.032
	(0.102)	(0.074)	(0.077)
Constant	-1.182	0.469	-0.722
	(0.865)	(0.506)	(0.494)
Observations	404	404	404
Wald test of exogeneity	10.03	25.16	25.03
p-value for Wald test	0.007	0.000	0.000
F-stat (Friends' participation)	60.49		
F-stat (Own participation)	10.26		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors, clustered by network, in parentheses.

Table 9: Marginal Effects: Female Bargaining Power

	Works Outside Household	Has Name on NREGS Card	Doesn't Need Permission
Effect of Friends' Participation on Non-participants	0.157**	-0.198 ***	0.182***
	(0.066)	(0.038)	(0.032)
Effect of Friends' Participation on Participants	0.054	-0.022	0.025
	(0.041)	(0.018)	(0.017)
Effect of Own Participation on Participants	-0.379	0.695***	-0.527***
	(0.422)	(0.173)	(0.203)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors, clustered by network, in parentheses.

487 women; 299 participants, 188 non-participants.

Table 10: Gender Differences in Standardized Bowls of Food Consumed by Children Younger than 21 in the Past 24 Hours: Instrumented Household Fixed Effects

	Rice	Lentils
Friends' Participation*Female Child	-0.067	0.226**
	(0.088)	(0.092)
Friends' Participation*Own Participation*Female Child	0.217	-0.221
	(0.201)	(0.226)
Own Participation*Female Child	-0.658	0.891
	(0.869)	(0.867)
Child Sex	0.143	-0.870**
	(0.552)	(0.424)
Child Age	-0.002	-0.003
	(0.012)	(0.014)
Constant	2.393***	2.269***
	(0.144)	(0.132)
Observation	594	595
F-stat (Friends' participation)	28.43	
F-stat (Own participation)	8.35	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors, clustered by network, in parentheses.

This sample consists of 295 boys and 300 girls under the age of 21.

Table 11: Marginal Effects: Peer Effects in Girls' Food Consumption

	Rice Consumption	Lentils Consumption
Friends' Participation on Non-participants' Daughters' Food Consumption	-0.067	0.227**
	(0.088)	(0.092)
Friends' Participation on Participants' Daughters' Food Consumption	0.149	0.005
	(0.146)	(0.186)
Effect of Own Participation on Daughters' Food Consumption	0.082	0.133
	(0.499)	(0.340)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors, clustered by network, in parentheses.

487 women; 299 participants, 188 non-participants.

Table 12: Mechanisms in Female Bargaining Power Regressions: Social Learning

	Works Outside Household	Has Name on NREGS Card	Doesn't Need Permission
Friends' Participation	0.613***	0.109	0.625***
	(0.146)	(0.411)	(0.191)
Friends' Participation*Low Education	-0.369***	-0.580***	-0.341**
	(0.117)	(0.212)	(0.144)
Friends' Participation*Own Participation	-0.528***	-0.292	-0.576***
	(0.201)	(0.313)	(0.108)
Friends' Participation*Own Participation*Low Education	0.375**	0.489**	0.360**
	(0.146)	(0.210)	(0.183)
Own Participation	0.525	4.461***	0.594
	(0.549)	(1.703)	(0.535)
Own Participation*Low Education	-0.653	0.275	-0.668
	(0.488)	(0.401)	(0.434)
Low (<= 4 years) Education	0.507	0.484	0.363
	(0.715)	(0.344)	(0.368)
Spousal Age Difference	0.043	-0.016	0.038***
	(0.028)	(0.040)	(0.014)
Own Age	0.013	-0.004	0.011
	(0.013)	(0.015)	(0.008)
Years of Education	-0.015	0.003	-0.024
	(0.044)	(0.039)	(0.021)
Number of Children	0.046	-0.069	0.045
	(0.059)	(0.111)	(0.060)
Age of Children	-0.009	0.049	-0.015
	(0.036)	(0.033)	(0.013)
Lives with In-laws	0.115	0.532**	0.067
	(0.186)	(0.236)	(0.153)
Brahmin	-0.066	-1.490***	-0.065
	(0.374)	(0.533)	(0.368)
Asset Index	-0.031	0.072	-0.012
	(0.117)	(0.148)	(0.078)
Constant	-0.905	-2.263**	-0.729
	(0.881)	(0.911)	(0.465)
Observations	404	404	404

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors, clustered by network, in parentheses.

Table 13: Mechanisms in Female Bargaining Power Regressions: Social Influence

	Works Outside Household	Has Name on NREGS Card	Doesn't Need Permission
Friends' Participation	0.575***	-0.683***	0.674***
	(0.160)	(0.190)	(0.174)
Friends' Participation*Spouse Age Difference	0.029	-0.036***	0.036**
	(0.018)	(0.012)	(0.014)
Friends' Participation*Own Participation	-0.462**	0.623***	-0.610***
	(0.197)	(0.134)	(0.131)
Friends' Participation*Own Participation*Spouse Age Diff.	-0.048***	0.038***	-0.041**
	(0.015)	(0.014)	(0.018)
Own Participation	1.254*	-0.131	1.325*
	(0.736)	(1.190)	(0.701)
Own Participation*Spouse Age Difference	0.223***	-0.092	0.183**
	(0.080)	(0.112)	(0.081)
Low (<= 4 years) Education	0.179	0.254	-0.242
	(0.492)	(0.175)	(0.204)
Spouse Age Difference	-0.077	0.056	-0.100
	(0.069)	(0.075)	(0.070)
Own Age	0.019*	-0.011	0.013*
	(0.011)	(0.007)	(0.007)
Years of Education	0.017	0.018	-0.014
	(0.041)	(0.014)	(0.018)
Number of Children	0.023	-0.070*	0.018
	(0.056)	(0.041)	(0.058)
Age of Children	0.012	0.024	-0.007
	(0.027)	(0.015)	(0.010)
Lives with In-laws	0.130	0.056	-0.035
	(0.150)	(0.182)	(0.153)
Brahmin	-0.120	-0.221	-0.105
	(0.325)	(0.190)	(0.302)
Asset Index	-0.092	0.020	-0.016
	(0.104)	(0.065)	(0.068)
Constant	-1.717**	0.736	-1.257**
	(0.696)	(0.703)	(0.508)
Number of Observations	404	404	404

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors, clustered by network, in parentheses.

Table 14: Mechanisms in Household Fixed Effects: Gender Differences in Standardized Bowls of Food Consumed by Children Younger than 21 in the Past 24 Hours

Social Learning	Rice	Lentils
Friends' Participation*Female Child	-0.032	-0.001
	(0.151)	(0.080)
Friends' Participation*Mother Low Education*Female Child	-0.019	0.295***
	(0.186)	(0.084)
Friends' Participation*Own Participation*Female Child	0.120	0.102
	(0.313)	(0.163)
Friends' Participation*Own Participation*Mother Low Ed. *Female Child	0.677	0.419
	(0.508)	(1.209)
Own Participation*Female Child	-0.675	-0.666
	(1.392)	(0.774)
Own Participation*Mother Low Education*Female Child	0.162	1.399
	(1.760)	(1.931)
Mother Low Education*Female Child	-1.639	-2.808
	(1.638)	(1.819)
Female Child	0.266	0.197
	(0.762)	(0.407)
Child Age	-0.003	-0.002
	(0.012)	(0.013)
Constant	2.389***	2.248***
	(0.135)	(0.126)
Social Influence	Rice	Lentils
Friends' Participation*Female Child	-0.036	0.135
	(0.077)	(0.085)
Friends' Participation*Spouse Age Difference*Female Child	0.003	-0.010
	(0.006)	(0.010)
Friends' Participation*Own Participation*Female Child	0.053	-0.083
	(0.236)	(0.247)
Friends' Participation*Own Participation*Spouse Age Difference*Female Child	-0.020	0.009
	(0.022)	(0.020)
Own Participation*Female Child	-0.374	0.552
	(0.825)	(0.825)
Own Participation*Spouse Age Difference*Female Child	0.010	0.038
	(0.064)	(0.061)
Spouse Age Difference*Female Child	0.030	0.012
	(0.046)	(0.048)
Female Child	0.245	-0.522
	(0.520)	(0.367)
Child Age	-0.002	-0.001
	(0.013)	(0.014)
Constant	2.387***	2.244***
	(0.151)	(0.140)
Observations	594	595

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors, clustered by network, in parentheses

This sample consists of 295 boys and 300 girls under the age of 21.

Table 15: Block-level Data from Indian Censuses of 1991 and 2001 on Female Bargaining Power

Variables	Untreated	Treated	Difference	t-test	Observations
Sex Ratio (M/F)	1.02	0.99	-0.02	-0.52	47
	(0.03)	(0.02)	(0.04)		
Sex Ratio 0-6 (M/F)	1.07	1.05	0.02	1.76	47
	(0.01)	(0.01)	(0.01)		
Ratio of Scheduled Caste Pop (M/F)	1.06	1.04	0.02	0.61	47
	(0.03)	(0.01)	(0.03)		
Ratio of Scheduled Tribe Pop (M/F)†	0.34	0.32	0.01	0.08	47
	(0.14)	(0.09)	(0.17)		
Literacy Ratio (M/F)†	1.05	1.08	-0.03	-1.86	47
	(0.01)	(0.01)	(0.02)		
Ratio of Total Workers (M/F)†	1.05	1.01	0.04	1.75	47
	(0.02)	(0.01)	(0.03)		
Ratio of Main Workers (M/F)†	1.09	1.04	0.05	1.73	47
	(0.03)	(0.01)	(0.03)		
Ratio of Non-workers (M/F)	0.87	0.95	-0.09	-1.57	47
	(0.05)	(0.02)	(0.05)		

†The distributions of the underlying variables for this ratio were significantly different from normal; they were thus logged and the ratio of the resultant variables was used here.
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$