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Expanding Horizons: Can Women's Support Groups Diversify Peer Networks in Rural India?

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Why peers matter: social networks in status, learning and influence (Eeshani Kandpal, The World Bank, Organizer)

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Peer networks provide their members new information about employment opportunities (Munshi and Rosenzweig 2006), shape available economic opportunities (Skoufias, Lunde, and Patrinos 2009), supply marital partners (Banerjee et al. 2009), facilitate adoption of new technologies (Conley and Udry 2010; Montgomery and Casterline 1996). Montgomery and Casterline distinguish between two key effects of social networks: information and influence. In both cases, homophily-induced homogeneous networks may limit the network's ability to affect social norms or at least delay the process, since information and social norms are likely already common to the network, and may well presumably 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, Kohler, and Watkins 2002; Golub and Jackson 2011, 2010).

Data on social networks can be difficult and expensive to collect. As a result, scholars have successfully exploited the correlation between networks and (1) community ties in Mexican migrants to the US (Mckenzie and Rapoport 2010), (2) kinship ties in Africa (Luke and Munshi 2006), and (3) caste in South Asia (Munshi and Rosenzweig 2006) to proxy for information on actual networks. However, economic growth, migration, and government interventions can diversify networks by introducing individuals from different groups or castes to each other. In such instances, the ability of caste or family groupings to identify the impact of networks can be quite limited, and may even decrease over time.

In India, in particular, the hierarchical structure imposed by the caste system means that peer networks are often restricted by caste. These constraints can potentially limit women's interactions to a small subset of the community. Access to outside role models has been demonstrated to improve women's bargaining power (Jensen and Oster 2009). In this paper, we use primary data on women's peer networks in Uttarakhand, India to first ask whether participants in a community-level women's empowerment program — *Mahila Samakhya* — have more diversified peer networks. Second, we ask whether caste is in fact a good proxy for social networks.

Mahila Samakhya organizes women into groups to provide formal, informal, and vocational education, and support groups with the explicit aim of empowering women to have a greater say in their households and communities. These group meetings increase female mobility and expand peer networks, and make participants' lives less solitary. These groups also introduce women from different castes and socioeconomic strata of society to each other. Thus, we expect to find less clustering by caste in the networks of participants than of non-participants.

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Uttarakhand and The *Mahila Samakhya* Program

Background on Uttarakhand

Uttarakhand is in the Indian Himalayas; villages tend to be remote and are often without basic infrastructural facilities, like government schools and hospitals. Small, scattered villages without access to roads conspire to limit the diversity of social contact. 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 cities. Uttarakhand has a large Hindu population — 85 percent as compared to 80 percent for the entire country (Census of India 2001). 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. As a result, networks in the area are fairly homogenous and stratified by caste (Mawdsley 1996).

Uttarakhandi women face severe restrictions on social and physical mobility. They tend to have very 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 women reported not having the final say on visits to family and friends (IIPS and ORC Macro 2007). Our field tests and 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. This state of isolation and ignorance accompanied by constricting social norms restrict women to the narrow spheres of family and housework.

Mahila Samakhya in Uttarakhand

Mahila Samakhya is a women's empowerment program that started in what is now Uttarakhand in 1995. 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. However, 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 join the program despite family opposition. Further, as the husbands and in-laws observe the benefits from participation, particularly through enhanced employability and increases in household income, they gradually reduce their opposition. Village- and district-level meetings allow participants to step outside their homes and villages, making their lives less solitary. 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.

Data

We collected data from the north Indian state of Uttarakhand on networks, and factors influencing network size and composition. In addition, we also collected data on participation in *Mahila Samakhya*, and household characteristics. Program centers have been present in Uttarakhand villages in six of thirteen Uttarakhand districts, allowing us to use the variation in exposure to identify changes in networks resulting from participation.

The data are from six Uttarakhand districts, four with the program and two without. The sample size is 487 women. When field testing the questionnaire, most 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 the sample. Hence, we employed restricted snowball sampling: we interviewed a randomly-chosen woman and asked her to list her five closest friends, and then conducted follow-up interviews with two randomly-selected women from these five friends. Our instrument includes the

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

Variables	Observations	Mean	Std. Dev	Min	Max
Friends of Other Castes	487	0.23	0.56	0	2
Respondent's Age	472	32.18	8.11	20	65
Husband's Age	437	37.89	9.25	23	80
Respondent's Age at Marriage	463	19.25	3.34	1	30
Average age of sons	487	8.05	7.79	0	36
Average age of daughters	487	6.18	6.70	0	30
Respondent's Years of Education	397	8.82	4.06	0	17
Husband's Years of Education	414	10.13	3.68	1	17
Sons' Years of Education	443	7.04	4.34	1	17
Daughters' Years of Education	355	6.73	4.23	1	17
Number of Rooms	487	3.33	2.12	0	19
Electrification	487	0.89	0.31	0	1

following key questions: (1) Who are your five closest friends and how do you know these people? (2) Do you participate in the *Mahila Samakhya* intervention? For how long has the program been in your village? (3) How important is it to you what your friends think of you? (4) What caste do you belong to?[1] (5) How old are you? How old is your husband? (6) What is your level of education? Are you literate? We also collected information on other characteristics including the complete birth history of the woman, the number of rooms in the house and the primary source of lighting. These questions help us identify the effect of participation in *Mahila Samakhya* on the network diversity of participants and non-participants.

Summary Statistics

As table 1 shows, the average woman in our sample was 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.

The second through fourth columns of table 2 indicate the presence of self-selection into *Mahila Samakhya*. The average participant is three percentage points closer in age to her husband than the average non-participant in treated districts, which suggests that women with greater initial bargaining power may self-select into the program. Further, participants tend to have older and more sons than non-participants, although the differences are not quite significant. Participants are less likely to live with their husbands; the difference of 19 percent is highly significant. Participants are also close-to-significantly less likely to live with their parents-in-law, and are significantly more likely to be Brahmin than non-participants. Finally, without controlling for any other characteristics, we do observe that participants have significantly more friends from outside their caste than do non-participants.

Several other characteristics, such as the number and age of daughters, the spousal education ratio, and the woman's time to collect water, are not statistically different for participants and non-participants. Further, none of the wealth indicators, including number of rooms, electrification, improved toilet facilities, materials used in floor and wall construction, are different for these two groups, suggesting that 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). Nonetheless, this table highlights the importance of controlling for selection in to the *Mahila Samakhya* program.

In addition, the last three columns of table 2 show us key characteristics of the four treated and two untreated districts in the sample. Few significant differences between the average characteristics between treated and untreated districts exist, thus, it appears that the program is not targeted in placement. The only significant difference is in the number of sons; on average, women in participating districts have 0.27 sons more than women in

[1] For this analysis we restrict ourselves to self-reported castes to minimize the reporting bias from using proxy reports (Hogset and Barrett 2010). Hence, we are limited to studying the seven women in each network with whom we conducted interviews.

Table 2. Basic Characteristics of Participants and Non-participants in Treated Districts Using a Women's Empowerment Study, Uttarakhand, India, 2009–2010

	Participants and Non-participants			*Treated and Untreated Districts*		
Variables	Non-part.	Part.	Diff.	Non-part.	Part.	Diff.
Demographics						
Other caste friends	0.194	0.233	−0.042	0.245	0.234	0.011
	(0.05)	(0.04)	(0.07)	(0.12)	(0.05)	(0.11)
Spousal age ratio	0.84	0.86	−0.03	0.85	0.85	−0.03
	(0.01)	(0.01)	(0.080)**	(0.01)	(0.01)	(0.02)
Age at marriage	18.48	19.17	−0.69	19.76	18.69	1.08
	(0.38)	(0.21)	(0.42)	(0.05)	(0.54)	(0.81)
Age of sons	7.26	8.97	−1.71	6.96	9.03	−2.07
	(0.77)	(0.50)	(0.95)	(0.84)	(0.76)	(1.25)
Age of daughters	6.33	6.54	−0.21	5.45	6.98	−1.52
	(0.73)	(0.44)	(0.84)	(0.46)	(0.84)	(1.29)
No. of sons	1.16	1.37	−0.21	1.09	1.38	−0.29
	(0.09)	(0.06)	(0.11)	(0.04)	(0.08)	(0.13)*
No. of daughters	0.98	1.14	−0.16	0.99	1.13	−0.14
	(0.08)	(0.07)	(0.12)	(0.05)	(0.07)	(0.11)
Spousal educ. ratio	0.66	0.58	0.07	0.65	0.61	0.03
	(0.05)	(0.03)	(0.05)	(0.12)	(0.04)	(0.09)
Lives with husb.	0.85	0.67	0.19	0.83	0.76	0.07
	(0.04)	(0.03)	(0.06)**	(0.09)	(0.09)	(0.04)
Lives with in-laws	0.55	0.44	0.12	0.56	0.45	0.11
	(0.05)	(0.03)	(0.06)	(0.11)	(0.04)	(0.09)
Works	0.52	0.59	−0.06	0.45	0.65	−0.08
	(0.05)	(0.03)	(0.06)	(0.07)	(0.12)	(0.18)
Brahmin	0.06	0.20	−0.14	0.21	0.14	0.07
	(0.03)	(0.03)	(0.05)**	(0.21)	(0.06)	(0.16)
Wealth Indicators						
No. of Rooms	3.09	3.30	−0.21	3.58	3.07	0.51
	(0.21)	(0.13)	(0.26)	(0.49)	(0.29)	(0.53)
Electricity (No = 0)	0.89	0.89	0.00	0.90	0.88	0.02
	(0.03)	(0.02)	(0.04)	(0.004)	(0.05)	(0.08)

Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

non-participanting districts. The magnitude of the difference suggests the economic impact, if any, is small. Thus, while participants might select into *Mahila Samakhya*, evidence suggests that the program is not targeted by geographic area in any meaningful way. Further, poorer participants appear to 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).

Empirical Analysis

Methodology

To understand how an intervention like *Mahila Samakhya* affects the composition of peer networks, and therefore whether caste is an unbiased proxies for networks, we compare the number of friends from castes other than the individual's caste for participants and untreated women. Note that because treated and untreated districts are not significantly different, treatment assignment (program placement) appears to be random, assuming unobservables are distributed as observables. That said, women still choose to participate in the program, which results in selection bias. Since the variation in network composition comes from participation, we must control for self-selection.

First, we use Propensity Score Matching (PSM) to account for self-selection into the *Mahila Samakhya* program. When treatment assignment or participation is not random but determined by observables, PSM allows us to compare treated individuals to untreated individuals (or non-participants in treated and untreated districts) using observables such as demographic and economic characteristics to construct the control group. Each individual in the dataset is assigned a propensity score that tells us the likelihood of an individual being treated. To minimize the issues from self-selection, we match treated individuals are matched to untreated ones based on proximity of their propensity scores, thus creating a control group. We then estimate the difference in the outcome of interest for treated and control groups. PSM eliminates selection bias to the extent that observables explain the decision to participate. We use kernel matching in which all treated observations are matched with a weighted average of the propensity score for all control observations. Weights are inversely proportional to the distance between the propensity scores of treated and control observations (Becker and Ichino 2002).

As a second approach to the problem of selection, we use 2SLS on the matched sample obtained from propensity score matching. We instrument for participation in *Mahila Samakhya* using the number of years the village has had the program interacted with the woman's age minus sixteen, because the youngest participant we encountered in our field tests or data collection was sixteen (however, older women can send their daughters to the program's girls' education centers). This variable tells us the years of exposure to the program, and is thus correlated with participation. Further, any effect of this variable on female empowerment likely works through participation in the program, rather than directly. This variable is driven by the year the program started in the village as there is little migration among married women in the region. Since women often migrate at the time of marriage, and we do not know whether the woman's natal village had the program, migration at the time of marriage might lead to measurement error, which in turn would bias results downwards. However, unmarried women do not participate in the program, so exposure would have to be indirect, and thus the resultant bias would be small.[2]

Our explanatory variables for the match and 2SLS regression comprise observed factors that likely affect both program participation and network composition: (1) the individual's caste (2) spousal age ratio, (3) years of education, and whether she literate (and is thus likely to need the education provided by the program), (4) how much she cares about her friends' opinion of her (reflecting her interest in community-level interventions such as *Mahila Samakhya*), (5) the number and age of her children, (6) whether she lives with in-laws and sisters-in-law, reflecting both her degree of autonomy in the household and her ability to leave young children at home while participating in the intervention, (7) the amount of time she spends each day in collecting firewood, which is exogenously determined since Uttarakhand is patrilocal. The time spent on firewood collection depends on the location of the house relative to neighboring forests, and reflects the amount of time a woman would have to participate in the program, (8) the number of rooms in her house to reflect wealth, and (9) whether her house has electricity. Village fixed effects are also included. We tried various specifications and matching metrics for the matching process; results are robust.

Results

Table 3 presents the treatment effect estimates from matching participants to women with similar characteristics from untreated districts. The results tell us that participants in the *Mahila Samakhya* program are significantly more likely to have more friends of other

Table 3. Estimated Differences in the Network Composition of *Mahila Samakhya* Participants and Untreated Individuals Using a Propensity Score Matching on Data from a Women's Empowerment Study, Uttarakhand, India, 2009–10

	Number of Other Caste Friends
	Unmatched
Participants	0.245
Untreated	0.254
Difference	−0.008
	(0.067)
	Matched
Participants	0.245
Untreated	0.09
Difference	0.157
	(0.091)**

Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

[2] While we restrict our main analysis to friends for whom we collected primary data via follow-up interviews. As a robustness test, we tried estimating these regressions with the proxy reports on the caste of all the friends listed by each woman. While the results are qualitatively similar, the significance dropped. This discrepancy further highlights the importance of using primary reports on networks.

castes than women in districts without the program. In other words, we see evidence that the community-level intervention succeeds at diversifying networks. The goodness of caste as a signifier of networks is thus limited for participants, and might even decrease over time as within-network contagion continues to change the network composition of participants. As a robustness test, we also compared the number of other caste friends of non-participants and untreated women to find no significant differences, indicating that non-participants do not have significantly more diverse networks simply by living in treated districts.

Table 4 presents results from the 2SLS estimation. These results tell us that *Mahila Samakhya* participants have a significantly larger number of friends from other castes, i.e. that their networks are more diverse than those of non-participants. Relative to women of other religions (who were treated as having only friends of different castes), all women reporting castes and Hindu women who did not report a caste had fewer friends of other castes. This result is not surprising and likely reflects the fact that Uttarakhand is even more dominantly Hindu than the rest of the country. Older women had fewer other caste friends, which is another intuitive result because these women are probably most entrenched in the social norm. Women with more children had fewer other caste friends, while women with older children had more other caste friends, perhaps reflecting differences in time constraints. Women who spend more time collecting firewood and those who care more about their friends' opinion of themselves have more other caste friends. Controls for household socioeconomic characteristics, including whether the woman lives with her in-laws, the number of

Table 4. 2SLS Results: *Mahila Samakhya* Effect on Network Diversity of Matched Sample

	Number of Other Caste Friends	t-statistic
Participation in *Mahila Samakhya*	0.179***	2.95
No Caste Reported	−1.832***	−5.67
Brahmin	−1.699***	−5.35
Rajput	−1.859***	−5.92
Scheduled Caste/Tribe	−1.863***	−5.87
Age	−0.007**	−2.00
Spousal Age Ratio	0.384	1.14
Number of Children	−0.094**	−2.07
Age of Children	0.017***	3.10
Lives with In-laws	0.046	0.84
Lives with Sister-in-laws	0.273	0.55
Time Spent Collecting Firewood	0.0003**	2.05
Years of Education	−0.005	−0.80
Literate	0.096	1.35
Importance of Friends' Opinion	0.221***	4.44
Number of Rooms	−0.045	−1.34
Is House Electrified?	−0.092	−0.79
Rooms*Electrified	0.041	1.16
Constant	1.640***	3.70
Observations	432	

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
The Constitution of India categorizes the lower castes and tribes as Scheduled Castes and Tribes.

Table 5. First Stage of 2SLS on Matched *Mahila Samakhya* Sample from a Women's Empowerment Study, Uttarakhand India, 2009–10

	Participation in *Mahila Samakhya*	t-statistic
LN(Potential Exposure to Program)	0.074***	30.38
No Caste Reported	−0.249	−1.43
Brahmin	0.11	0.63
Rajput	−0.089	−0.52
Scheduled Caste/Tribe	0.063	0.36
Age	−0.0003	−0.17
Spousal Age Ratio	−0.062	−0.34
Number of Children	−0.015	−0.62
Age of Children	0.002	0.58
Lives with In-laws	−0.059**	−2.02
Lives with Sister-in-laws	0.010	0.04
Time Spent Collecting Firewood	−0.0003***	−4.15
Years of Education	0.012***	3.55
Literate	−0.068	−1.78
Importance of Friends' Opinion	0.035	1.28
Number of Rooms	−0.020	−1.10
Is House Electrified?	−0.135**	−2.15
Rooms*Electrified	0.024	1.26
Constant	0.538**	2.25

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
The Constitution of India categorizes the lower castes and tribes as Scheduled Castes and Tribes.

rooms in the house, and whether the house has electricity do not appear to influence network composition.

First stage results of the 2SLS regression, presented in table 5, tell us that the instrument (natural log of potential exposure to the program) is significantly positively correlated with program participation, while living with in-laws, and time spent collecting firewood are negatively correlated. Women who live with their in-laws may have less freedom to participate in empowerment programs, while those who have to spend more time away from the village probably have less time to participate. More educated women are significantly more likely to participate.

Conclusion

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, which is often skewed to the male in the household. Diversifying networks may improve female bargaining power of those women in the network by allowing them to connect with role models, facilitating information sharing with women who have a different range of experiences, or challenge the social norms in which they usually find themselves. We find that *Mahila Samakhya* was able to diversify social networks, as measured by having friends outside one's caste. Thus, we see evidence that policy-makers can harness network-based learning to change social norms.

Our results also speak to the use of caste and extended family to proxy for social networks, and may raise concerns about bias if caste or family networks are used as proxies to measure the effect of a treatment that may itself affect the diversity of networks. While using caste and extended family may be completely appropriate in rural, conservative settings, if the treatment being measured might affect network diversity, a rigid proxy for network connections may bias the effect of the network on the outcome. Previous analyses that have relied on caste or other signifiers like community or kinship ties to study the impact of networks on the migration decision, marriage, or the availability of jobs might thus have underestimated the network effect by relying on these proxies.

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