Mothers' Social Networks and Socioeconomic Gradients of Isolation

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I. Introduction

"To engage in . . . social interaction[s]" and "to live with and toward others" are basic capabilities essential for human dignity and freedom (Nussbaum 2011). Social networks and social interactions are crucial for broad aspects

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of well-being and are key drivers of economic outcomes.[1] The role of personal networks for economic outcomes is particularly important in low-income contexts where they often provide informal insurance (as stressed, among others, by Townsend 1994 and Munshi and Rosenzweig 2016) while also playing a key role in the diffusion of information about technological innovations, as discussed by Banerjee et al. (2013).[2]

In this paper, we describe the social connections or lack thereof between younger married women in rural Odisha, India. Social ties with other women may be important in increasing women's support for more gender-equitable norms (Kabeer 1994; Rowlands 1997). The support that these ties provide and the collective action they enable are critical for social and political movements that empower women, both in their homes and in their broader communities (Sanyal 2009; Prillaman 2023).[3] Therefore, isolation may be part of a vicious cycle that entrenches the disadvantages that women face in terms of political representation and their voice and involvement in decision-making in their households and communities. Likewise, because social networks are important transmitters of information (Kohler, Behrman, and Watkins 2000, 2007; Kohler and Bühler 2001; Behrman, Kohler, and Watkins 2002; BenYishay and Mobarak 2019; Beaman et al. 2021), isolation may limit women's knowledge, particularly of heavily gendered subjects such as sexual and reproductive health or child development (Anukriti et al. 2020; Anukriti, Herrera-Almanza, and Karra 2024), that are not typically discussed by married couples or within male social networks (Mason and Smith 2000) and which may be particularly pertinent around pregnancy and motherhood. Networks can also be an important means of access to capital, markets, and insurance (e.g., Fafchamps and Lund 2003; Feigenberg, Field, and Pande 2013; Field et al. 2016; Barnhardt, Field, and Pande 2017), implying that isolation may limit women's business endeavors and economic well-being.

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[1] On the relationship between networks and mental well-being and life satisfaction, see Berkman et al. (2000), Cacioppo and Hawkley (2003), De Silva et al. (2007), Fowler and Christakis (2008), and Sawyer, Ayers, and Smith (2010).

[2] For example, the role of networks in providing insurance is analyzed by Ambrus, Mobius, and Szeidl (2014), Attanasio and Krutikova (2020), and Ambrus, Gao, and Milán (2022).

[3] A recent review by Díaz-Martin et al. (2023) found positive effects on women's decision-making in roughly half the evaluations of women's groups they studied.

The important linkages between women's social connections and their freedoms, mental health, empowerment, and access to information raise several questions about women's social connections in contexts that have strict gender norms. How connected or isolated are women on average, and how does this change over time? What is the depth of the social connections that women do have? How does connectedness or isolation vary by women's socioeconomic status? What drives socioeconomic gradients in isolation?

In this paper, we address some of these questions by documenting the social ties of 2,170 married women who have young children and live in 192 villages of Odisha, India. This group may face particular barriers to building and maintaining social connections with peers. The custom of brides moving into their husbands' households upon marriage coupled with women typically marrying outside of their own communities (patrilocality) means that young women typically lose their adolescent and familial social networks upon marriage. Moreover, strong gender norms that frown upon married women moving freely about their communities or working outside the home mean that married women may find it hard to create and maintain new ties with peers in their new communities (Miller 1982; Chen 1995; Field et al. 2021; Jayachandran 2021), which is further affected by the presence of a mother-in-law (Anukriti et al. 2020). Restrictions on men and women from different households socializing mean that married women do not have access to their husbands' social networks.

We follow the same women over 4 years and measure on a yearly basis not only the number of connections they have but also the depth of these connections. We asked up to 12 mothers who have children between the ages of 1 and 20 months in each village whether and how well they knew each of the other interviewed mothers in the village. On average, we interviewed a (quasi-randomly selected) 45% of mothers who have children in this age range within a village. The median mother in our sample knew just 1, or 11%, of the other mothers we asked about despite the other mothers living on average just 237 meters away. Moreover, 39% of mothers reported that they did not know any other mother in our sample. An extrapolation exercise to account for the fact that we asked about only a fraction of other mothers in the village suggests a median within-village peer group size of 3.2. Additional data, collected 7 years after the first wave and 3 years after the last, suggest that other young women living in close proximity, and indeed primarily in the same household, are the main social network for young mothers in our sample, suggesting a very small overall network. We also document that in-person interactions are the main form of contact and that mobile phone or online communication is very rare. This is similar to other contexts where women of similar ages and circumstances represent an important source of advice and support (Richardson, Barbour, and Bubenzer 1995).

Furthermore, this group represents a key margin of network-size adjustment. Whereas other components of one's networks, such as familial or caste ties, are fixed, the network of one's peers is more likely shaped by the individual.

The high level of social isolation that women face in rural India has previously been documented in qualitative studies (Sanyal 2009; Crivello et al. 2018) and, more recently, also in quantitative studies (Kandpal and Baylis 2019; Anukriti et al. 2020; Anukriti, Herrera-Almanza, and Karra 2024). The degree of isolation we find is consistent with these past studies. An important contribution of this work is that the panel nature of the data allows us to document the persistence of this isolation over a 4-year period. Further, in addition to data on the existence of connections, we have rich data on the strength of connections and frequency of interactions that enables us to paint a detailed picture of women's social lives. Finally, our study captures social networks around new motherhood, a particularly crucial life stage for both women and their children.

We next describe the socioeconomic gradient of isolation and examine its correlates. We might expect social and economic characteristics, such as caste and poverty, to intersect with gendered norms and restrictions, resulting in differences in the types and strengths of women's social networks by their socioeconomic status (SES). It is, however, not obvious in which direction this gradient would go. For example, mothers from higher-SES households might acquire more social connections if their high status makes them a valuable connection that others seek out and if time devoted to social connections is something that only women from more-advantaged households can afford. Conversely, more-affluent women may be less-"valuable" connections or may benefit less from social connections if, for example, they are less involved in agricultural production and hence can less likely serve as a source of information (Magnan et al. 2015). More-advantaged households may also be able to "afford" to adhere to more-restrictive gendered roles for women. This may lead to women in more-advantaged households facing more restrictions to their mobility because these households may not have to rely on women's work outside the home to meet basic economic needs and can afford amenities such as indoor gas stoves and private toilets. Previous work has found that women from both more-advantaged castes (Boserup 1989) and wealthier households (Chen 1983) face more restrictions than their less-advantaged peers. Many studies have found that, in India, women's participation in paid work outside the home declines rapidly as other sources of household income, including men's earnings, rise (Kapadia 1995; Eswaran, Ramaswami, and Wadhwa 2013; Klasen and Pieters 2015; Mehrotra and Parida 2017; Chatterjee, Desai, and Vanneman 2018). This strong income effect on women's labor force participation is consistent with the idea that women not working is something that households value highly and opt

for readily when economically and practically feasible. It has long been noted that in South Asia, women not leaving the home and not being in public spaces often brings social status to households (Miller 1982; Chen 1995; Klasen and Pieters 2015). Having concrete reasons to leave home and be in public spaces, either for work or for other needs, may well be crucial for allowing mothers to make and maintain social connections.

In practice, we observe a negative socioeconomic gradient in connectedness: we find that mothers from richer households and those from more-advantaged castes and tribes are more isolated than their peers from poorer households and less-advantaged castes and tribes. The additional data we collected suggest that mothers of higher SES do not engage in more interaction through mobile phones or online interactions. To the best of our knowledge, this is the first quantitative study to examine the socioeconomic gradient of women's social isolation.

We next analyze the drivers of the SES gradients we observe. We decompose the gradients in three parts: first, the SES composition of villages; second, differences by SES in women's propensities to have social connections within their SES group; and third, SES differences in women's propensities to have ties across SES groups (i.e., differences in the degree of homophily). Our data suggest that the second component is the chief driver of both the caste/tribe and the wealth gradients: higher-SES women are substantially less likely to know the other higher-SES women in their village than lower-SES women are to know the other lower-SES women. The negative relationship between wealth status and connections also holds within caste/tribe groups. Social ties across SES groups are less common than those within groups, indicating substantial homophily, but this is equally the case for higher- and lower-SES mothers. Village composition can explain about a third of the observed caste/tribe gradient. To the best of our knowledge, this is the first study to offer such a decomposition of the drivers of heterogeneity in network size.

Finally, we examine correlates, or "mediators," of homophily and of SES differences in within- and across-group social ties. We find that the higher rates of toilet ownership among higher-SES households are associated with a substantial portion of both the homophily we observe and the lower within-group connectedness of high-SES women (by both wealth and caste/tribe). Toilet ownership means that women are less likely to have to defecate in the open. However, in this context, for the sake of safety, women often form informal groups with whom they travel out of the house to more isolated areas of the village to defecate, which opens up opportunities for social interactions (Patil 2019). Together, we interpret the mediation of isolation with toilet ownership as evidence that actions that households take as they get wealthier may end up worsening women's

isolation. A similar conclusion is drawn from an analysis of labor force participation. This paper contributes toward building a new strand of literature on the drivers of women's isolation in contexts that have strong gender norms. Recent work has suggested that women's isolation is intensified through living with a mother-in-law (Anukriti et al. 2020) or geographic relocation (Barnhardt, Field, and Pande 2017).

Our paper proceeds as follows. In section II, we discuss the study context and data, section III documents the features of social networks in this context, and section IV concludes.

II. Study Context and Data

The setting for this study is rural Odisha, India. This state in eastern India is poorer and more rural than the country as a whole: it has an income per capita of around US$1,300, and 33% of the population lived below the poverty line in 2018 (Government of Odisha 2018). According to the 2011 census, 17.1% of the population belongs to a scheduled caste, which is greater than the national proportion (16.6%), while the proportion belonging to a scheduled tribe, at 22.9%, is far greater than the national average (8.6%).[4]

This study uses primary data gathered as part of a randomized controlled trial of an early-childhood intervention in 192 villages across three blocks (districts) of Odisha: Balangir (in Balangir district), Soro (Balasore) and Salepur (Cuttack) (see fig. A1; figs. A1–A3 are in app. A, available online). The study sample consists of a panel of 2,170 mothers who have infants between the ages of 1 and 20 months at the time of the first survey (wave 1) in November 2015 and has an average of 11 study participants per village.[5]

We generated our sample as follows. We first identified the participants who met the study's eligibility criteria, which were based on the requirements of the early-childhood intervention (for more details, see Attanasio et al. 2016). Pregnant women and mothers who have children under the age of 2 years were identified through a census of each village in the summer of 2015, just prior to wave 1 of the study. The sample was split into two groups: target children, who met the age criteria for the intervention (between 7 and 16 months

[4] Odisha figures from the 2011 census are taken from https://www.censusindia2011.com/odisha-population.html. Note that social interactions in Hindu communities in India continue to be influenced by the caste hierarchy. A detailed discussion of this complex system is beyond the scope of this paper; however, several authors have written about how it especially influences the lives of rural women (Byres, Kapadia, and Lerche 1999; Chakravarti and Krishnaraj 2018).

[5] Where the mother was not the primary caregiver of the child, we collected information on both mothers and primary caregivers. This occurred in 8.4% of cases. For cases where the biological mother is still alive, we used her as part of the networks module; where this was not the case, we replaced her with the primary caregiver.

at the start of the intervention), and spillover children, who would be aged just above or just below the age criteria (1–6 and 17–20 months). In villages where there were fewer than eight eligible target children (roughly 38% of villages), all eligible children were selected. Villages with more than eight eligible target children had a median of 15 eligible children. In these villages, one child was selected at random, and that child's seven nearest neighbors were then targeted for enrollment.[6] This geographic approach to sampling was chosen to facilitate intervention implementation. However, because it meant that more-central households were more likely to be selected, a legitimate concern is whether this method may have systematically undersampled groups with certain socioeconomic characteristics who might be more likely to live on the outskirts of villages. If this were the case, it could bias our estimates of connectivity. To check this concern empirically, in table A1 (tables A1–A7 are in app. A) we assess how representative our chosen sample is of all those who have children in this age range in these villages by using the census data. In particular, we use the census data on all eligible target children (those whom we estimated would be between 7 and 16 months at the start of the intervention) and regress indicators of whether or not we selected respondents for inclusion on indicators of caste, household size, and two proxies of wealth.[7] We see that none of these characteristics appears correlated with whether or not the respondent was selected for inclusion, and this continues to hold true once we look within villages by including village fixed effects. While these results are reassuring, we show that our main findings are robust only to use of the 38% of villages where there were eight or fewer target children and therefore where we did not perform any within-village selection.[8]

Spillover children were selected by creating a list of all other children under 2 years of age in the village ordered by average distance from the randomly chosen central target child. A total of four spillover children per village from the ordered list were enrolled in the sample, choosing first children who were closer to the age range of intervention eligibility.[9]

[6] All surplus children (children in the eligible age range who lived further than the first seven children from the central child) were placed on a reserve list and were added to the sample only if one of the targeted households had left the sample area between the census and wave 1 or refused the survey and were added in order of distance from the central child. This occurred in around 14% of cases.

[7] Because we only collected a very limited set of variables in the census, we have only particularly crude measures of wealth. The only two proxies we have are whether the household has a mobile phone and whether the household lives in a multistory building.

[8] In particular, table A3 replicates table 2, while table A4 replicates table 3.

[9] This was done with the following order of priority: up to three 5-to-6-month-old children; up to two 17-to-18-month-old children; all other 5-to-6-month-olds; all other 17-to-18-month-olds; all

TABLE 1
SAMPLE CHARACTERISTICS IN WAVE 1

Variable	Mean	SD	Observations
Household economic characteristics:			
Number of household members	5.46	2.36	2,170
Household under US$1.90 per day poverty line (2019 USD; proportion)	.93	.25	2,167
Household owns a toilet	.47	.50	2,167
Household has a ration card	.65	.48	2,164
Household engaged in agriculture	.68	.47	2,163
Household main room has dirt floor	.43	.50	2,167
Household owns a refrigerator	.19	.39	2,166
Household social characteristics:			
Scheduled caste or tribe and OBC (proportions)	.62	.49	2,161
Khandayata or Brahmin	.21	.41	2,161
Hindu	.92	.28	2,166
Muslim	.08	.27	2,166
Mother and child characteristics:			
Mother age (years)	25.4	4.38	2,162
Years since first child born	3.33	3.69	2,024
Grades of schooling attained	7.38	3.50	2,169
In labor force	.06	.24	2,167
Distance from other sample mothers within village (meters)	237.4	213.38	2,168

This generated an overall sample for wave 1 (target and spillover children combined) of 2,170 children who have ages between 1 and 20 months and are from 10–12 households in each village (1,401 target, 769 spillover). Because households of target and spillover children are observationally equivalent on key margins (see table A2), we make no distinction between the two groups.

Mothers were reinterviewed in three further surveys in November 2016 (wave 2), November 2017 (wave 3), and March 2019 (wave 4). In the summer of 2022, we collected additional data by phone to obtain information on wider social networks.[10] Because our aim is to describe the social networks of young mothers in the absence of the treatment, we use data from all 2,170 mothers in wave 1 (pretreatment) but use data from only the 532 mothers in the 48 control villages when analyzing dynamics in networks.

The characteristics of sample mothers and their households in wave 1 are given in table 1. Mothers in our sample are young and poor and have an average age of 25 years; 6% of mothers work, and the average household per capita income per day is $US0.84 (2019 USD); 93% live below the US$1.90 per day international poverty line. About 65% of the households hold a ration

other 4-month-olds and under; and all 19-to-20-month-olds. The quota of spillover children was filled by using this order of priority when spillover children targeted for enrollment refused the survey.

[10] The choice to conduct a phone rather than face-to-face survey was driven by budget considerations as well as the COVID-19 pandemic.

card, for which only the poorest households are eligible. Households on average live 237 meters from each other and constitute about a third of total mothers who have children under 30 months in their village. We asked each respondent for the religion and the caste or tribe of the household head, which was then categorized into scheduled caste (SC), scheduled tribe (ST), other backward castes (OBC), dominant caste (Brahmin or Khandayata), or other. Sample households are 92% Hindu and 8% Muslim. Our sample is predominantly SC/ST/OBC (62%) with a significant minority identifying as the upper (dominant) caste (21%). In what follows, we categorize SC/ST/OBC households as belonging to a "disadvantaged caste or tribe."

In each survey wave, we collected detailed data on the social network among study participants. Each respondent was asked "Do you know [NAME]?" for each other survey member in the respondent's village.[11] If a respondent answered affirmatively to knowing another participant, we asked a series of follow-up questions relating to the intensity of their relationship. These questions spanned a range of topics such as the duration of the relationship, whether or not the respondent spoke about her own children, and whether the respondent could borrow food from this person.[12] These data provide a detailed picture of not only who knows whom but also how well they know each other. We additionally collected each household's geographic location using the Global Positioning System (GPS) and cross-checked measurements over the multiple survey waves to reduce measurement error.[13]

It is important to consider the implications of our sampling strategy for our network data. Our social-networks data are incomplete in two senses. First, in villages where not all mothers are included in the sample, we might underestimate the size of their "peer network." To gauge this degree of underestimation, we conduct an exercise to extrapolate the patterns of connectivity we see in the partial network to the complete village network of mothers of children aged under 30 months as captured in the census data (for details, see app. C). We find

[11] In wave 1, this list was populated with the 12 mothers targeted for inclusion in the study on the basis of the census. However, not all these mothers were actually enrolled (due to refusals, incorrect information about the children's ages having been recorded during the census, or the interviewers being unable to relocate the house). This implies for the dyad-level analysis, where we require characteristics of both the respondent and the mother asked about, we have a smaller analysis sample than for the general analysis of social connectedness. In waves 2–4, the list was populated with the actual study participants.

[12] For full module, see app. B; apps. A–C are available online.

[13] We primarily used GPS measurements taken at the census carried out at the start of the study. However, in cases where these coordinates suggested that a respondent lived more than 1 km from the nearest neighbor, we manually compared these measures with those taken at later rounds and took the measure that appeared most reasonable.

that we capture on average one-third of the total peer network. In wave 1, mothers self-reported their total peer-network size. Our extrapolation is lower than the self-reported total number of known mothers (which is 6.3 on average), in line with literature suggesting that asking about named individuals rather than aggregate number of connections is more precise (McCormick et al. 2010; Breza et al. 2020). In our main analysis, we therefore use the reported number of named individuals but show robustness to our results by using the estimated total network of mothers in table A5. The results are in line. The second implication of our sampling strategy for mothers' networks relates to its location-based nature, which implies that our mothers are on average physically closer to each other than would be the case if they were selected at random. This selection might therefore bias upwards our estimates of connectivity in the complete network, implying that the degree of isolation could be underestimated. As discussed above, we show in table A1 that our sample is representative at the village level along various margins. A limitation of our study remains that we cannot test representativeness in terms of networks. We do show, however, that our results hold when focusing only on villages where we did not need to do location-based sampling.

Finally, our network data are incomplete in the sense that we analyze connections to only other mothers of young children. To assess the extent to which this peer-group network reflects the mothers' total social network, we fielded additional data collection when their children were about 7 years old. In particular, we asked mothers about how many people they know with whom they can relax and have fun with and how many they know with whom they can talk when being down or depressed. We also asked them about the frequency of interaction by mobile phone or online (including through text messaging, WhatsApp, Facebook, etc.) and about their agreement with the statement that "Most of my social interactions are with members of my household."

Figure 1 shows examples of village networks in wave 1. Figure 1*A* shows an example of a village network selected randomly from the sample: each dot represents a respondent plotted on a Cartesian coordinate system on the basis of her geographic position in the village and the village center at (0,0), and each arrow represents a connection from one respondent to another. The direction in which the arrow points represents the direction of the reported connection. This village is smaller than average and had five target children and four spillover children identified as part of the census. An advantage of the way we collect network data is that we are able to detect asymmetric or unreciprocated connections, making the captured network more precise (Breza et al. 2020). Figure 1*A* makes clear that many reported connections are unreciprocated

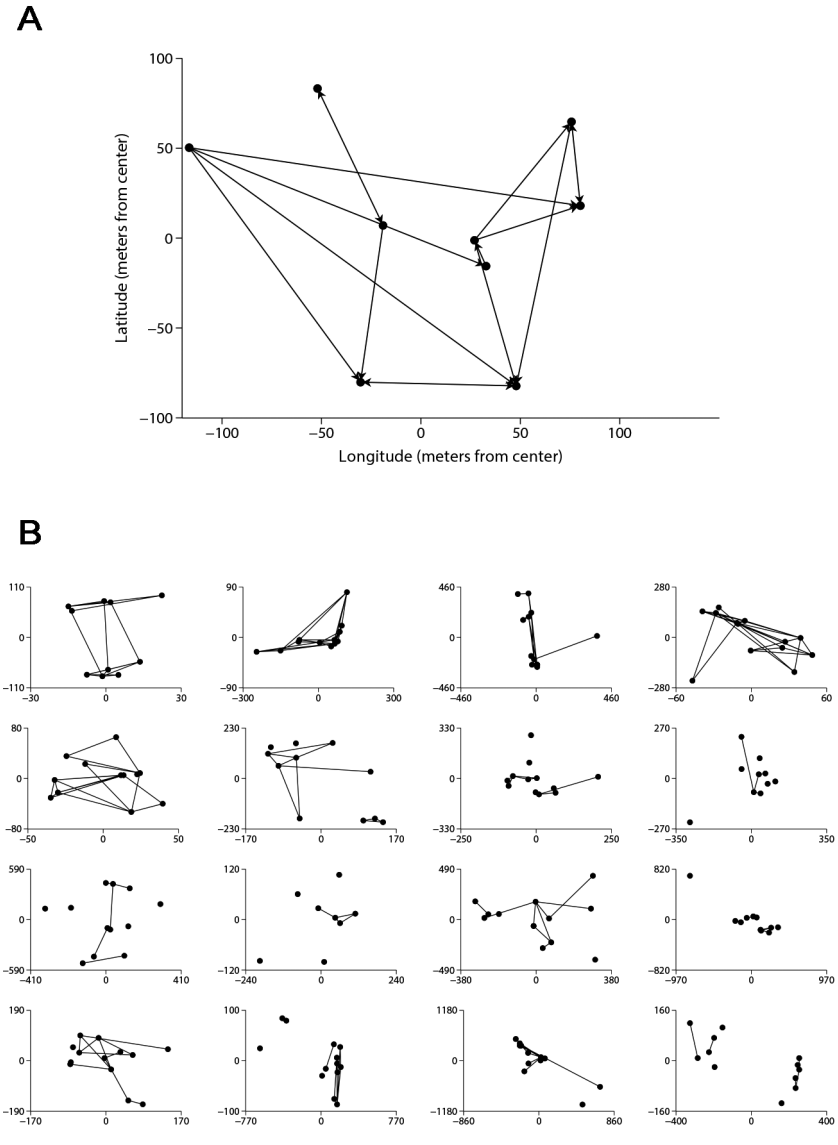


Figure 1. Seventeen randomly selected network graphs from wave 1. *A*, Directed network graph for a single randomly chosen village. *B*, Undirected network graphs from random selection of 16 villages in wave 1 of data collection. Mothers are positioned according to their geographic position in the village, and the x- and y-axes show meters from the village center along the longitude and latitude dimensions, respectively.

(around 48% in wave 1). Given that the question we used to form these connections asked about whether the respondent knew the other mother, it is perfectly feasible that some respondents knew who the other mother was or had a brief acquaintance with her but that the connection was not reciprocated. For

example, if some women are particularly prominent in the village, they may have many inward connections but know relatively few others. The fact that many connections are unreciprocated highlights a point we make later in the paper, which is that even the connections that do exist (and defined so broadly—just an acquaintance) often appear weak in terms of how well individuals report knowing one another.

Figure 1*B* shows 16 other randomly selected villages displayed in the same way, where lines between respondents indicate any connection between the two. Figure 1*B* shows that there is considerable heterogeneity in the geographic spread of the sample in different villages, with many containing small subhamlets where a few households live outside of the main village.

III. Isolation and Its Socioeconomic Gradient

A. Isolation

1. Number of Connections Reported

We examine outward connections (that the mother identifies between herself and other mothers in the village sample) and inward connections (where other mothers have reported a connection with a particular sample mother within the village). Figure 2 shows the distribution of outward connections for all respondents in wave 1. The first feature of social networks in this sample is their sparsity. Out of an average of 11 possible connections within a village, in the control group the average number of connections reported is 1.21, the

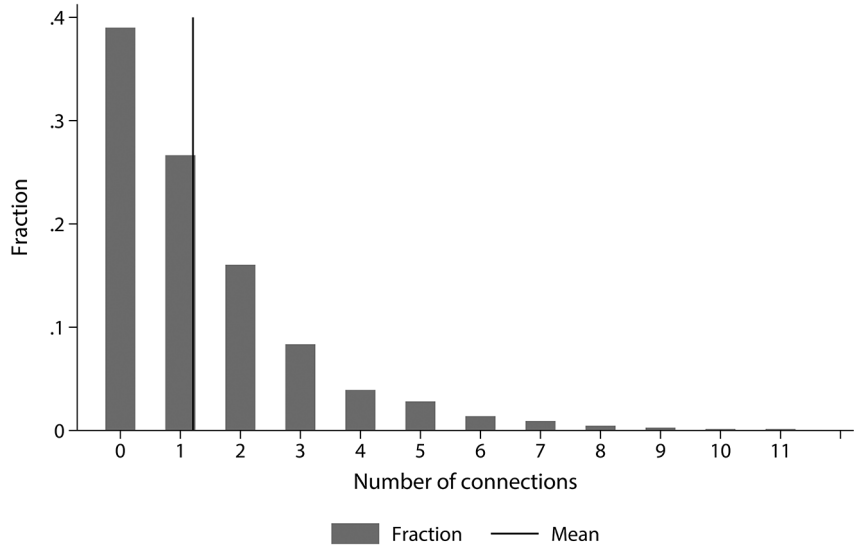


Figure 2. Distribution of connections in wave 1.

TABLE 2
NETWORK SIZE BY WAVE IN THE CONTROL GROUP

	All Observations			Balanced Panel		
Wave	Mean	SD	Observations	Mean	SD	Observations
1	1.21	1.54	530	1.28	1.57	455
2	1.01	1.28	487	1.02	1.26	455
3	1.79	1.70	486	1.82	1.71	455
4	2.07	1.95	490	2.09	1.91	455

Note. Shown are the means and SDs of the number of outward connections by wave in the control group. "All Observations" contains all observations, while "Balanced Panel" is a balanced panel of mothers who appear in every wave.

median is 1, and the mode is 0 (reported by 39% of sampled women). This number increases over time but remains relatively small, the mean network size being 2.07 by wave 4 (table 2).[14] We also show in table 2 that these patterns over time in network size are almost identical when we consider the balanced panel of mothers who appear in all four waves, reassuring us that patterns are not being driven by differential attrition.

2. Estimating Total Within-Village Peer Networks

A limitation of this exercise is that our data only contain connections between the mothers selected to be a part of the study. To estimate the average number of other mothers who have children of a similar age that respondents know in the whole village, we perform an out-of-sample prediction exercise. For the sample for which we have detailed network information, we estimate the probability that a connection exists between any two mothers (allowing the probability to vary with the children's ages, the mothers' ages, the mothers' castes, and the mothers' geographic proximity to one another).[15] We then use these probabilities to predict the likelihood that our respondents know each of the other mothers in the village who were identified in the census as having similarly aged children but whom we did not ask the respondent about. We then sum these probabilities to obtain an estimate of the total number of connections that mothers have, including those we did not directly inquire about. (See app. C for details of this method.) We estimate that each mother has an average of 3.2 connections to other mothers of similarly aged children in the village.

As an alternative to this extrapolation exercise, in wave 1 we additionally asked respondents how many other mothers they know inside the village who have children between 0 and 24 months of age. While the networks literature

[14] As discussed in n. 5, in waves 2–4 we asked about a different set of mothers. This may explain the reduction in total connections from wave 1 to wave 2.

[15] Since we did not have the same socioeconomic characteristics of nonsample mothers, we were unable to include socioeconomic characteristics as predictors in this exercise.

reports that asking about a random set of peers is the preferred elicitation method when cost is not a determining factor (Griffith 2022), the results show peer groups with a median size of 4 (see fig. A2). Considering the proximity of these households and the small communities in which they reside, these are strikingly small peer groups.

3. Out-of-Village and Online Connections

In the main survey waves, we have information only about social networks with other young mothers within the village. It could, therefore, be the case that although these young women are isolated from others in their situation in their immediate vicinity, they have other robust social networks that we are missing. In wave 1, we have some information about women's contact with their natal families. We plot these data in fig. A3*a*. The data confirm that patrilocality is indeed the overwhelming practice: for the 94% of respondents whose in-laws are still alive, the woman lives in the same village as her in-laws, but for only 9% of the respondents, the woman lives in the same village as her mother.[16] We further see that women's connections with their natal families are limited. For instance, the median woman living in a different village from her mother had seen her mother only four times over the past 12 months. We observe similar patterns for seeing siblings. These data suggest that women's strong in-person connections with their natal families are unlikely to be compensating for a sparse social network within their marital villages.

This still leaves uncertain whether young women have other connections, and in particular whether they have connections (either to their natal families or to other people) over mobile phone or online that provide important sources of social support. To ascertain whether this holds true, we fielded some additional questions on a phone survey in 2022 that asked about the extent of women's networks outside the groups of other young mothers in their villages, which we plot in figure A3*b*. The first thing to note is that even after having lived in their husbands' villages for upwards of 7 years, 96% of mothers say that most of their social interactions are with members of their own households. Mobile phones or social media do not seem to reduce this degree of isolation. Eighty-six percent of mothers say they did not interact with anyone on mobile phone or online (including through text messaging, WhatsApp, Facebook, etc.) outside those of their immediate household in the past week. Those that did reported on average two such interactions in the past week. We conclude that women of similar ages and circumstances represent the key social network of

[16] We note that the wealth and caste gradients we observe in sec. III.C remain unchanged when we control for whether a woman lives in the same village as her mother and when we condition on those women who moved.

these women, in line with many other contexts where peers have been shown to be the primary source of advice and support (Richardson, Barbour, and Bubenzer 1995).

B. *Strength of Connections*

Figure 3 shows the strength of social ties that women in our sample report in wave 1. It displays the proportion of connections for which respondents report doing a certain activity together or being able to draw on the connection for support.

Of those we asked about, the most common shared activity was talking about young children (72%). This suggests motherhood is a defining identity in structuring young women's relationships in this context. Sixty percent of respondents reported having spoken to a given connection in the past 15 days. Only 29% had visited the connection's house during the same period. Given that the sample villages are small and respondents live close together, this suggests women have relatively infrequent contact, and even less frequent private contact, even with the connections that they do have. Only for 38% of connections did respondents report being able to talk about personal matters.

For some analysis, it is useful to summarize all information about how well members of such connections know each other into a single "connectedness" index defined between each mother and every other mother in the sample in her village. This index takes on a value between 0 (indicating the respondent

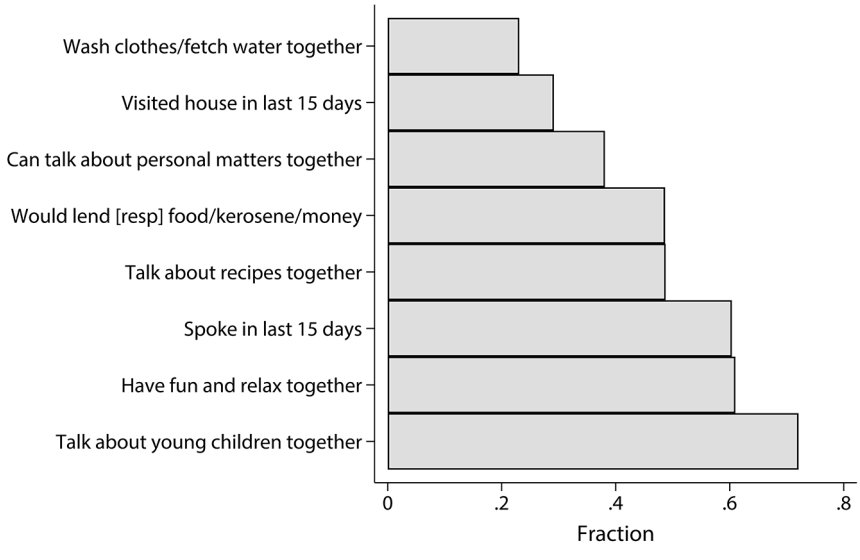


Figure 3. Strength of social ties (wave 1). The bar chart shows the fraction of times that (conditional on a connection existing) the respondent reports the connection meets each of eight criteria.

does not know that mother at all) and 1 (indicating that the respondent knows that mother and answered "yes" to every one of the indicators listed in figure 3). We create this indicator through a latent factor model. We model respondent i's response (Z_{ijk}) to each of the eight indicators, $k = \{1, \ldots, 8\}$, listed in figure 3 regarding other mother j as the following function of the underlying connectedness of mother i to mother j, θ_{ij}:

$$Z_{ijk} = \frac{\exp\left(a_k\theta_{ij} + b_k\right)}{1 + \exp\left(a_k\theta_{ij} + b_k\right)}.$$

Conditional on a connection existing between i and j at all, we assume that θ_{ij} is distributed normally with mean 0 and variance 1. This is a standard two-parameter item response theory (IRT) model. We estimate the parameters, $\{a_k, b_k\}$, through maximum likelihood. We then predict values of θ_{ij} for each i to j connection by taking the mean of the posterior distribution of θ_{ij} conditional on Z_{ijk} and the estimated parameters. So that we can also define a level for this connectedness index for connections that do not exist, we assume that a connection not existing is the same as a connection where none of the indicators about the strength of the connection is nonzero. Finally, we rescale the connectedness index to lie on the [0, 1] interval, where it takes the value 0 when $Z_{ijk} = 0$ for all k and the value 1 when $Z_{ijk} = 1$ for all k.

C. *Heterogeneity and the Socioeconomic Gradient of Connections*

We next explore heterogeneity in mothers' networks. As we saw in figure 2, there is considerable variation in the number of connections reported. The first thing we check is whether this variation exists within or between villages. In other words, is it just that some villages are much more densely connected than others or is it the case that even within villages there is heterogeneity in mothers' connectedness? A simple decomposition of variance suggests that 59.7% of the overall variance in reported connections comes from within-village variation. If we condition on mother's age, age of the eldest child, distance from the village center, and the number of children, 63.5% of the residualized variance comes from within-village variation.

We next consider how the size of mothers' networks varies by SES, specifically by wealth and caste and tribe.[17] Figures 4*A* and 4*B* plot, respectively, the

[17] An individual's wealth score is calculated by using a principal component analysis (PCA) of assets in wave 1. The principal component is calculated across, not within, villages. Across all groups, wealth is low, with an average per capita daily income of US$0.55 in the lowest wealth quintile compared with US$1.39 in the highest (2019 USD). While wealth and caste are significantly correlated (correlation coefficient of 0.24), there is a lot of variation in wealth within caste, and we therefore consider this to be a conceptually separate dimension of SES that is important to analyze.

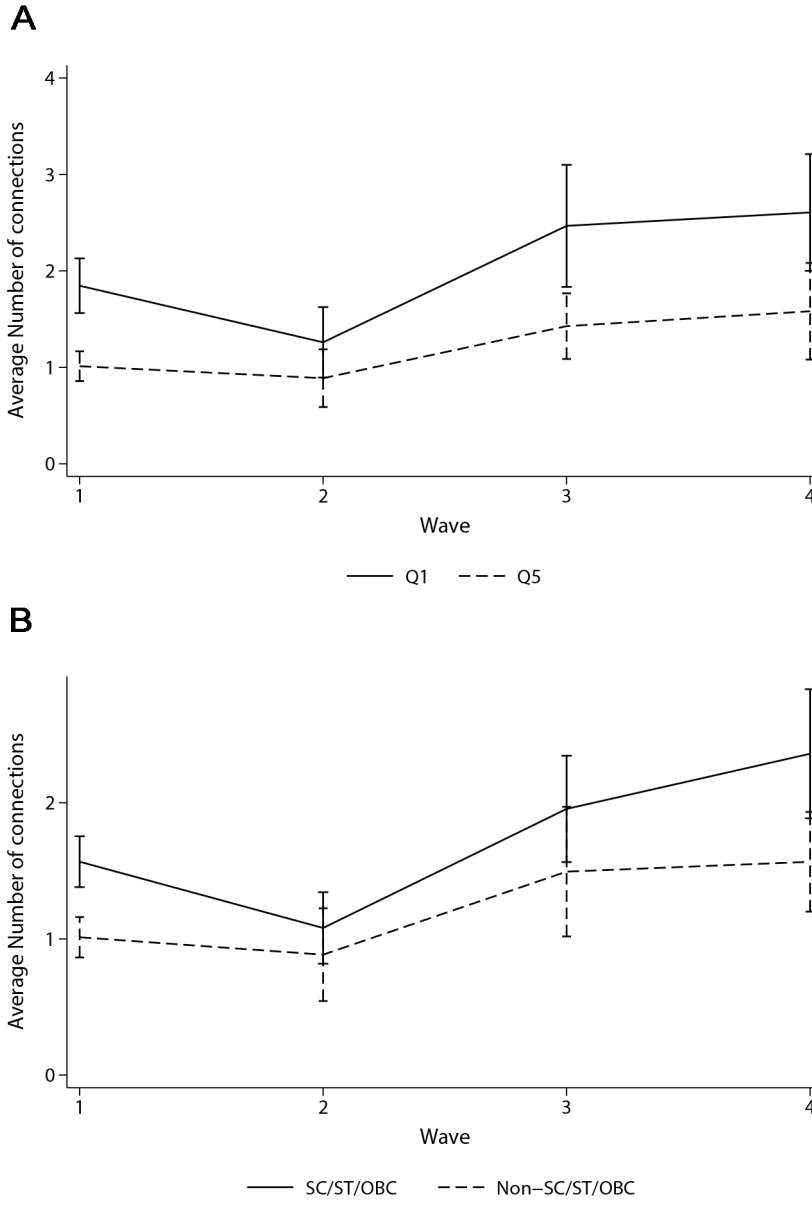


Figure 4. Socioeconomic gradient over time for controls. *A*, Network size and wealth quintile. *B*, Network size and caste or tribe. Averages include the whole sample in wave 1 and only control villages thereafter. Range bars indicate 95% confidence intervals.

average number of outward connections by wealth and by caste and tribe across the four survey waves for the controls. Across both dimensions of SES, there are large and persistent negative gradients in network size. Namely, poorer mothers and mothers from more-disadvantaged castes and tribes (SC/ST/OBC) report more connections than their wealthier peers and peers from more-advantaged castes or tribes (non-SC/ST/OBC). At wave 1, this amounted to an average of 0.90 fewer connections for mothers in the highest wealth quintile relative to the lowest and of 0.56 fewer connections for non-SC/ST/OBC women relative to SC/ST/OBC women. Given the median network size in wave 1 is 1, these differences are substantial.

Both panels of figure 4 show an increase in network size over time for each group, yet both the caste/tribe and wealth gradients persist, and arguably increase, between waves 2 and 4 and persist thereafter. This suggests that the determinants of these gradients are pertinent throughout the period in which mothers have young children.

We run a regression analysis of total network size at baseline against a series of covariates to estimate the conditional correlation between certain key characteristics and network size (table 3). In panel A of the table, the outcome variable is total outward network size, and in panel B, we weight each connection by its estimated "connectedness," the index between 0 and 1 defined in the previous subsection. This weighted measure thus combines both the number of connections and how well each connection is known.

Columns 1 and 2 of table 3 show us again what we saw in the above figures: dominant caste and wealthier women have fewer connections. While caste is a binary indicator, our wealth index is continuous, and figure 5*A* shows a bin scatter plot of the number of connections by the wealth indicator. We see evidence that average number of connections is monotonically decreasing in wealth across the whole of the wealth distribution. Column 3 of table 3 shows that women who had their first child longer ago (proxying for the length of time in the village) also have larger networks, which is what we would expect. Figure 5*B* plots a bin scatter plot of network size on time since the birth of the eldest child and shows that while the mean appears to be increasing throughout the distribution of child age, the rate of change decreases, suggesting that network size might plateau. Column 4 of table 3 shows that each of these dimensions (caste/tribe, wealth, and age of the eldest child) is statistically significant even when both are included in the regression, suggesting that all are important predictors of network size. Column 5 of table 3 shows that this effect of caste/tribe and age of the eldest child persists even when we control for covariates mother's age, number of children, and distance from the village center. These are important to control for because all these might systematically differ

TABLE 3

CORRELATES OF OUTWARD NETWORK SIZE AT WAVE 1

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Number of Outward Connections					
Wealth index	−.308***			−.198***	−.180***	−.0341
	(.0546)			(.0499)	(.0482)	(.0536)
SC or ST + OBC		.555***		.445***	.430***	.344***
		(.103)		(.0984)	(.0942)	(.0904)
Age of eldest child (years)			.0891***	.0748***	.0568***	.0527***
			(.0133)	(.0124)	(.0198)	(.0193)
Mother's age (years)					.00544	.00669
					(.0125)	(.0125)
Distance from sample center (km)					−2.269***	−2.177***
					(.256)	(.244)
Number of children					.0639	.0521
					(.0685)	(.0693)
Household owns toilet						−.521***
						(.0973)
Mother in labor force						.682***
						(.210)
Constant	1.354***	1.012***	1.040***	.817***	1.169***	1.405***
	(.0725)	(.0752)	(.0678)	(.0796)	(.287)	(.294)
Observations	2,153	2,144	2,153	2,144	2,139	2,139
	B. Number of Outward Connections Weighted by Connectedness					
Wealth index	−.204***			−.140***	−.136***	−.0530*
	(.0309)			(.0277)	(.0280)	(.0308)
SC or ST + OBC		.321***		.241***	.240***	.193***
		(.0613)		(.0573)	(.0576)	(.0540)
Age of eldest child (years)			.0469***	.0310***	.0218*	.0186
			(.00768)	(.00908)	(.0122)	(.0118)
Mother's age (years)					.00658	.00716
					(.00807)	(.00801)
Distance from sample center (km)					−1.243***	−1.182***
					(.160)	(.151)
Number of children					.0465	.0405
					(.0431)	(.0428)
Household owns toilet						−.291***
						(.0560)
Mother in labor force						.499***
						(.143)
Constant	.664***	.466***	.498***	.524***	.481***	.609***
	(.0412)	(.0451)	(.0398)	(.189)	(.182)	(.182)
Observations	2,153	2,144	2,153	2,139	2,139	2,139

Note. Shown are regression coefficients and standard errors (in parentheses) from regressing the number of outward connections an individual has (panel A) and that number weighted by how well that individual knows each connection (panel B) on wealth, caste/tribe, toilet ownership, age, and labor force participation.

* $p < .10$.

*** $p < .01$.

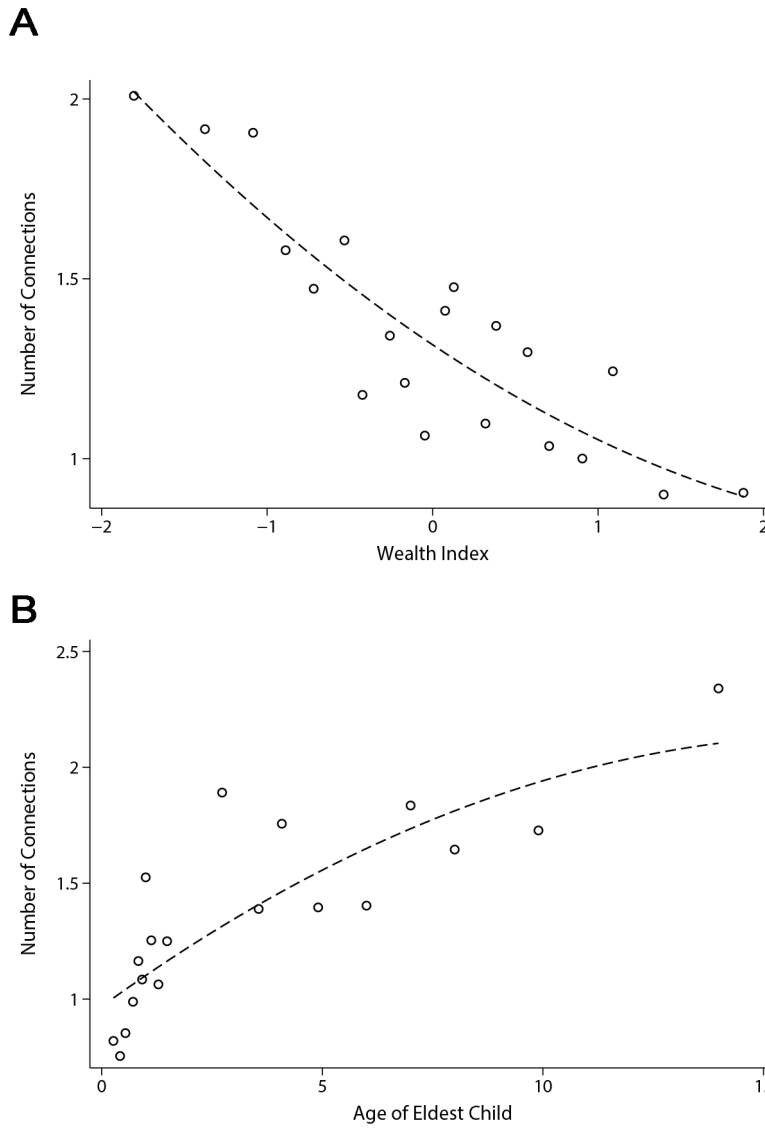


Figure 5. Relationship between number of outward connections, household wealth, and age of the eldest child. Shown are bin scatter plots between the number of connections reported and (*A*) the household's wealth index and (*B*) the age of the eldest child. In particular, we use 20 quantiles for both variables, and within each quantile, we plot the average number of outward connections. We also add a quadratic trend line.

by SES. Each of the three dimensions remains highly statistically significant and similar in size after controlling for these covariates. Over and above age of the eldest child, mother's age is not predictive of network size. Notably, network size is also strongly predicted by labor force participation, indicative of working mothers being more mobile around their villages.

Finally, in column 6 of table 3, we add further covariates that we might imagine are codetermined with networks including toilet ownership and labor force participation. Toilet ownership, even conditional on wealth, is associated with 0.52 fewer connections, likely due to women who own toilets not traveling with other mothers in their villages to defecate. Conditional on other covariates, the wealth index is not statistically significant, which could indicate that the effect of wealth is operating through these other characteristics, such as toilet ownership, labor force participation, and distance from the village center.

Moving to panel B of table 3, we see that these associations persist once we weight the number of connections by how well mothers know each other. Wealth conditional on other covariates is significantly negatively correlated with having a higher weighted number of connections, suggesting that after conditioning on other factors, higher wealth may be particularly associated with knowing connections less well. Finally, in table A5, we show that we also see the same large and highly statistically significant socioeconomic gradients in respondents' self-reports of their overall number of connections.

D. Who Knows Whom? Decomposing SES Gradients

Mechanically, the SES gradients we observe can be decomposed into three components:[18]

i. *Differences in within-group connectedness between SES groups*. Such differences could drive our SES gradients if high-SES women with young children were less likely than low-SES women to know other women within their own SES group. We define this component of the gradient as what can be attributed to differences in the within-group connectedness of low- and high-SES sample mothers: it is the portion of the gradient that would

[18] Denote higher- and lower-SES mothers as, respectively, H and L. Let $\bar{T}_H$ be the sample average of the total number of other sample mothers that the high-SES sample mothers know in each village. Mechanically, we have that $\bar{T}_H = \hat{p}_{HH} \times \bar{n}_{HH} + \hat{p}_{HL} \times \bar{n}_{HL}$, where $\bar{n}_{HH}$ and $\bar{n}_{HL}$ are sample averages of the total number of other high-SES sample mothers and of low-SES sample mothers living in villages where high-SES mothers live, and $\hat{p}_{HH}$ and $\hat{p}_{HL}$ are the in-sample probabilities that a high-SES mother reports knowing, respectively, another high-SES sample mother or a low-SES sample mother. Correspondingly, we have $\bar{T}_L = \hat{p}_{LL} \times \bar{n}_{LL} + \hat{p}_{LH} \times \bar{n}_{LH}$ with analogous definitions. Taking the difference and by rearranging terms, we can decompose the difference in the number of connections that low- and high-SES mothers report into

$$\bar{T}_L - \bar{T}_H = \underbrace{\bar{n}_{HH}(\hat{p}_{LL} - \hat{p}_{HH})}_{\text{(i) Within-group}} + \underbrace{\bar{n}_{HL}(\hat{p}_{LH} - \hat{p}_{HL}) + \hat{p}_{LL}(\bar{n}_{LL} - \bar{n}_{HH})}_{\text{(ii) Across-group}} + \underbrace{\hat{p}_{LH}\ (\bar{n}_{LH} - \bar{n}_{HL})}_{\text{(iii) Village composition effects}}.$$

The logic of this decomposition is similar to the Oaxaca-Blinder decomposition (Blinder 1973; Oaxaca 1973).

remain if village composition was symmetric (i.e., both SES groups lived in villages with the same number of potential within- and across-group connections) and if across-group connection rates were the same across groups.

ii. *Differences in across-group connectedness between SES groups*. Such differences could drive our SES gradients if high-SES women were less likely to know women from outside their SES group (low-SES women) than low-SES women were. This is the component of the gradient driven by differences in the rate at which low-SES sample mothers report knowing high-SES sample mothers and vice versa: it is the portion that would remain if village composition was symmetric and if within-group connection rates were the same across groups.

iii. *Village composition effects*. A final factor is that even with identical within- and across-group rates of connections, a negative gradient could result if the composition of the village is such that women of higher SES systematically live in villages where they are in the minority, and women of lower SES live in villages where they are in the majority. Under homophily (a higher rate of within-group vs. across-group connections), this would lead to an aggregate difference in the total number of connections even if high-SES and low-SES women were as likely as each other to know women of their own groups and outside their groups. We defined these village composition effects as the portion of the gradient that would remain if the between- and across-group connection rates were the same across SES groups.

With our detailed dyad-level data, we can provide an exact decomposition of the SES gradient into components driven by the three components. In this exercise, we again define high wealth and low wealth by the household being above or below the sample median value of a wealth index. This makes village composition effects (effect iii) irrelevant for explaining wealth gradients because, by definition, across the sample high- and low-wealth women live in villages with the same number of within- and across-group potential connections.[19]

We show results from this decomposition exercise in figure 6. Overall, we see that the largest share of both the wealth and the caste gradient comes from differences in within-group connectedness. Differences in the rate at which high- and low-SES women report knowing the other women in their village from their same SES group accounts for 61% of the caste gradient and 100%

[19] In practice, villages do not contain the identical number of other sample women, and so this is true for the proportions but not the numbers of women in their own and of the opposite wealth group. This is why we estimate a nonzero (but very small) village composition effect in fig. 6.

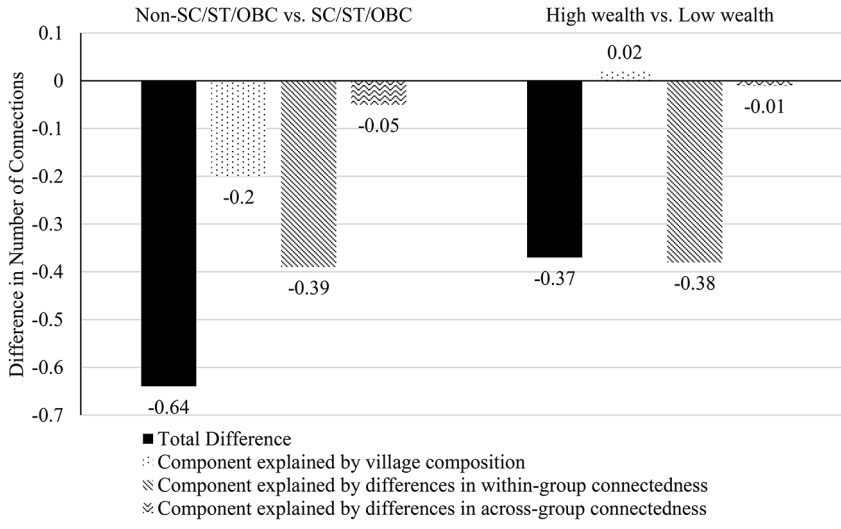


Figure 6. Decomposition of SES gradients in network size.

of the wealth gradient. By contrast, only 7% of the caste gradient is explained by differences in across-group connection rates, while this component plays no role for wealth.

These patterns can be seen in figures 7*A* and 7*B*, which plot the dyadic probabilities of connections within and across SES groups. Starting with within-group connections, we see that SC/ST/OBC sample mothers are substantially more likely than non-SC/ST/OBC mothers to report knowing a randomly chosen other sample mother from their village from their broadly defined caste/tribe group (23% vs. 15%; fig. 7*A*). Low-wealth mothers are substantially more likely than high-wealth mothers to report knowing a randomly chosen mother in their same wealth group (22% vs. 14%; fig. 7*B*).

Moving to across-group connections, the bottom two bars of figures 7*A* and 7*B* plot the across-group connectedness of sample mothers by caste/tribe and wealth, respectively. The probability of across-group connections is substantially lower than the probability of within-group connections. This is true along both the caste/tribe and the wealth dimensions and for both higher- and lower-SES mothers. Our social networks thus exhibit substantial homophily. For neither caste/tribe nor wealth do we see differences in the probability of across-group connections by mothers' SES. In other words, high-SES mothers are as likely to report knowing a randomly chosen lower-SES mother in their village as low-SES mothers are to report knowing a high-SES mother. This is why across-group differences contribute little to the overall SES gradients (fig. 5).

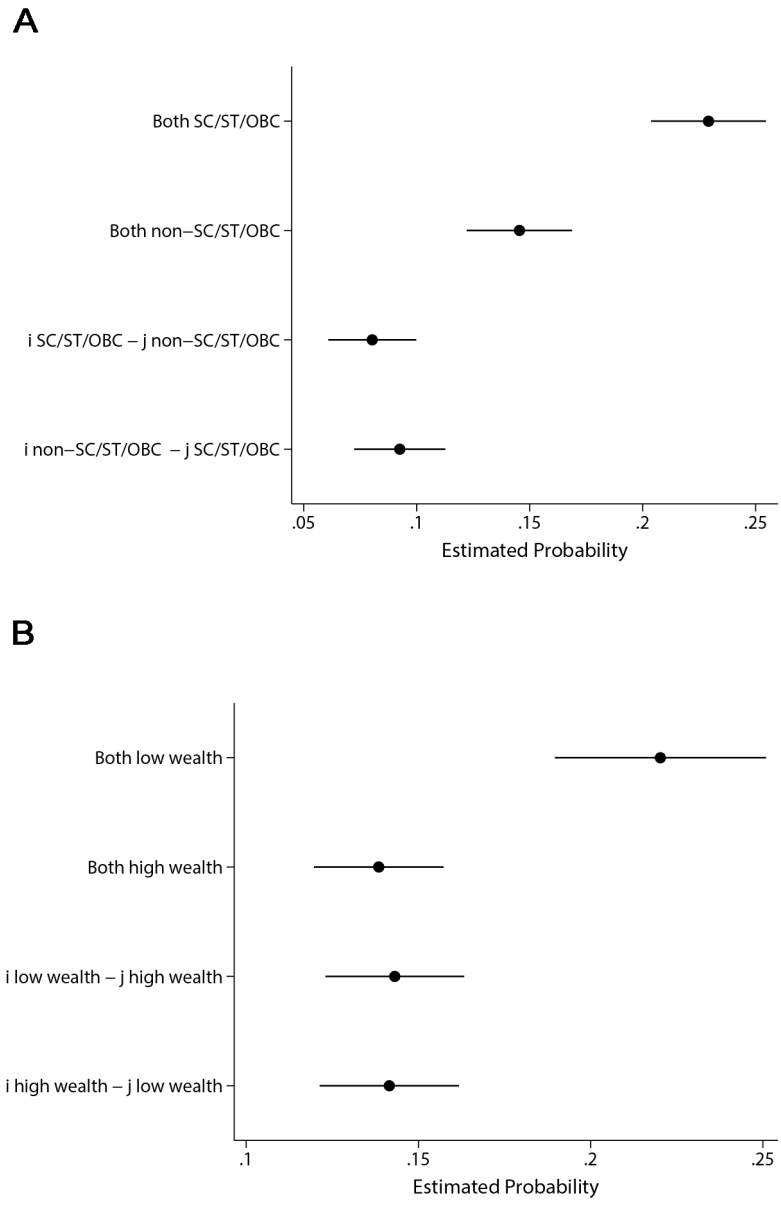


Figure 7. Dyad-level probabilities in wave 1. *A*, Caste/tribe. *B*, Wealth. Plotted (with 95% confidence intervals) is the probability that a respondent *i* reports knowing another respondent *j* depending on *i*'s and *j*'s caste/tribe and wealth.

The remaining component is what can be explained by village composition given identical within- and across-group connection rates. As noted earlier, because our wealth grouping is simply defined as being above or below the median on a wealth index, this is not relevant for the wealth gradient.[20] Village composition can, though, explain 31% of the caste gradient. Simple descriptive statistics tell us that SC/ST/OBC sample mothers, on average, live in villages with 6.0 other SC/ST/OBC sample mothers and 2.3 non-SC/ST/OBC sample mothers. This contrasts with non-SC/ST/OBC sample mothers who, on average, live in villages with 4.7 other non-SC/ST/OBC sample mothers and 3.5 SC/ST/OBC sample mothers. Even with identical probabilities of forming connections within and across groups, the fact that mothers from more-advantaged caste/tribe groups systematically live in villages with fewer other mothers from their own caste/tribe groups could contribute to the SES caste gradient we observe under homophily.

E. Mediating the Gap in Connectedness

Our decomposition exercise shows that differences in within-group connectedness can explain the majority of the negative SES gradients in connectedness by caste/tribe and by wealth; a lower within-group connectedness can explain the entirety of the wealth gradient and three-fifths of the caste/tribe gradient. In this section, we look at what mother characteristics correlate with the observed gradient to get a better idea of why lower-SES women have higher within-group connectedness than higher-SES women. One explanation could, for example, be that higher-SES women face more restrictions in interacting with peers, even peers of the same wealth and caste/tribe groups. These could stem from women in higher-SES households facing greater mobility restrictions, especially if it is less necessary for these women to leave the household frequently for work or for using the toilet.

To probe the relevance of such drivers of within- and across-group connectedness by caste/tribe and wealth, we conduct a mediation analysis, which helps us to assess whether other observed characteristics of respondents and the asked-about mother can mediate the observed SES gradients, using a dyad-level analysis. The approach we take, while routinely used, should be seen as descriptive in nature: control variables that can explain a portion of the SES gap do not necessarily themselves "cause" social connections; they may simply be correlated with underlying causes of connections (Rosenbaum 1984). A causal mediation

[20] The only reason we would see village composition playing a role for wealth would be differences in village sizes and/or differential nonresponse to the network questions. Reassuringly, then, our decomposition finds that village composition would predict a difference between the number of connections of high- and low-wealth women of just 0.02.

analysis would require an instrumental variable approach to control for the potential endogeneity of the mediators.[21] However, no credible instruments exist in our context, and we offer this mediation analysis as tentative evidence to stimulate further research on the topic.

We first regress, by ordinary least squares (OLS),[22] a binary indicator of whether or not a connection between mother i and mother j in village v exists (Y_{ijv}) on indicators of whether this is a low-to-high-SES connection (C_{ijv}^{LH}), a high-to-low-SES connection (C_{ijv}^{HL}), or a high-to-high-SES connection (C_{ijv}^{HH}) on the basis of i's and j's caste or wealth group, with the omitted group being low-to-low-SES connections:

$$Y_{ijv} = \beta_0 + \beta^{\mathrm{HH}} C_{ijv}^{\mathrm{HH}} + \beta^{\mathrm{LH}} C_{ijv}^{\mathrm{LH}} + \beta^{\mathrm{HL}} C_{ijv}^{\mathrm{HL}} + \epsilon_{ijv}.$$

We allow the error term, ϵ_{ijv}, to be arbitrarily correlated within the same village but assume independence across villages. These estimates are equivalent to those in section III.D. The term $\hat{\beta}^{\mathrm{HH}}$ is the difference between the probability of a high-SES mother having a randomly chosen within-group connection and the same probability for a low-SES mother (i.e., $\hat{p}^{\mathrm{HH}} - \hat{p}^{\mathrm{LL}}$). The term $\hat{\beta}^{\mathrm{LH}}$ ($\hat{\beta}^{\mathrm{HL}}$) is the difference between the probability of a low-SES (high-SES) mother having a randomly chosen across-group connection and the probability that a low-SES mother has a randomly chosen within-group connection, and thus it is equal to $\hat{p}^{\mathrm{LH}} - \hat{p}^{\mathrm{LL}}$ ($\hat{p}^{\mathrm{HL}} - \hat{p}^{\mathrm{LL}}$). The magnitudes of $\hat{\beta}^{\mathrm{LH}}$ and $\hat{\beta}^{\mathrm{HL}}$ are indicative of the degree of homophily, while the magnitude of $\hat{\beta}^{\mathrm{HH}}$ is indicative of the degree to which low-SES women have within-group connections at a different rate from that of high-SES women.

We sequentially add other characteristics of mother i (X_{iv}), mother j (X_{jv}), and their interactions ($X_{iv} \times X_{jv}$):

$$Y_{ijv} = \beta_0 + \beta^{\mathrm{HH}} C_{ijv}^{\mathrm{HH}} + \beta^{\mathrm{LH}} C_{ijv}^{\mathrm{LH}} + \beta^{\mathrm{HL}} C_{ijv}^{\mathrm{HL}} + \alpha_1 X_{iv} + \alpha_2 X_{jv} + \alpha_3 X_{iv} \times X_{jv} + \epsilon_{ijv}.$$

We observe how the unexplained differences in the probability of a connection existing (β^{HH}, β^{LH}, and β^{HL}) change as a result of adding these controls. This provides an indication of whether these observed characteristics can "explain" SES differences we see by caste/tribe and by wealth in the probability of having connections.

[21] See, e.g., the analysis of the role of parental investments as a mediator for an early-childhood intervention in Colombia (Attanasio et al. 2020).

[22] The benefit of using OLS over the probit estimator in this exercise is that we can use simple linear combinations of the β parameters to exactly recover the estimated probability of two individuals being connected and do not have to make assumptions about the distribution of ϵ_{ijv}. Repeating the analysis with probit yields almost identical results (available upon request).

Figure 8*A* shows how different characteristics mediate the gaps in probabilities of different groups reporting connections relative to the probability of the "SC/ST/OBC to SC/ST/OBC" connection. The figure starts with the caste/tribe-only model, sequentially adding wealth, age, household toilet ownership, maternal labor force participation, and finally the distance between respondents in the same village (quadratically). Though wealth and age are independently important predictors of connectedness, controlling for wealth and age does not substantially alter the gap between the within-group connectedness of SC/ST/OBC mothers and that of non-SC/ST/OBC mothers or the degree of homophily exhibited.

Controlling for household toilet ownership reduces the difference in within-group connectedness by caste/tribe by roughly 3 percentage points. It also reduces by a similar magnitude the difference existing between the probability of cross-group connections and the probability of within-group connections. Non-SC/ST/OBC households are more likely to own a toilet in our sample (64% vs. 36% for SC/ST/OBC) and thus are less likely to defecate in the open, something that women often do in a group (Patil 2019). This analysis suggests that this might be an important feature in explaining why women from non-SC/ST/OBC households have fewer within-group connections and why they both know fewer and are known by fewer SC/ST/OBC women. Labor force participation, while having little association above and beyond toilet ownership, if included separately is associated with a similar percentage of both within- and across-group connectivity. Labor force participation among sample women is rare but marginally more common among SC/ST/OBC women (6.2% vs. 6.0%). Taken together, these results suggest that the lower mobility of non-SC/ST/OBC women is associated with their smaller social networks.

Controlling for distance between respondents reduces the difference between the probability of cross-caste/tribe connections and the probability of within-group connections by around 4 percentage points, suggesting it could be an important driver of caste/tribe-based homophily. However, distance is associated with none of the difference in within-group connectedness by caste/tribe conditional on all other covariates. Villages in our sample are segregated by caste and tribe, with the average distance between mothers of different groups being 339 meters relative to only 244 meters for mothers of the same groups, in line with the general practice of families from different castes and tribes residing in different parts of the village (or even different villages). This framework does not allow us to determine the causal relationship between distance and network size; villages could be segregated because households do not want to form ties across caste/tribe lines, and segregated villages could simultaneously limit the opportunities for individual connections to be made.

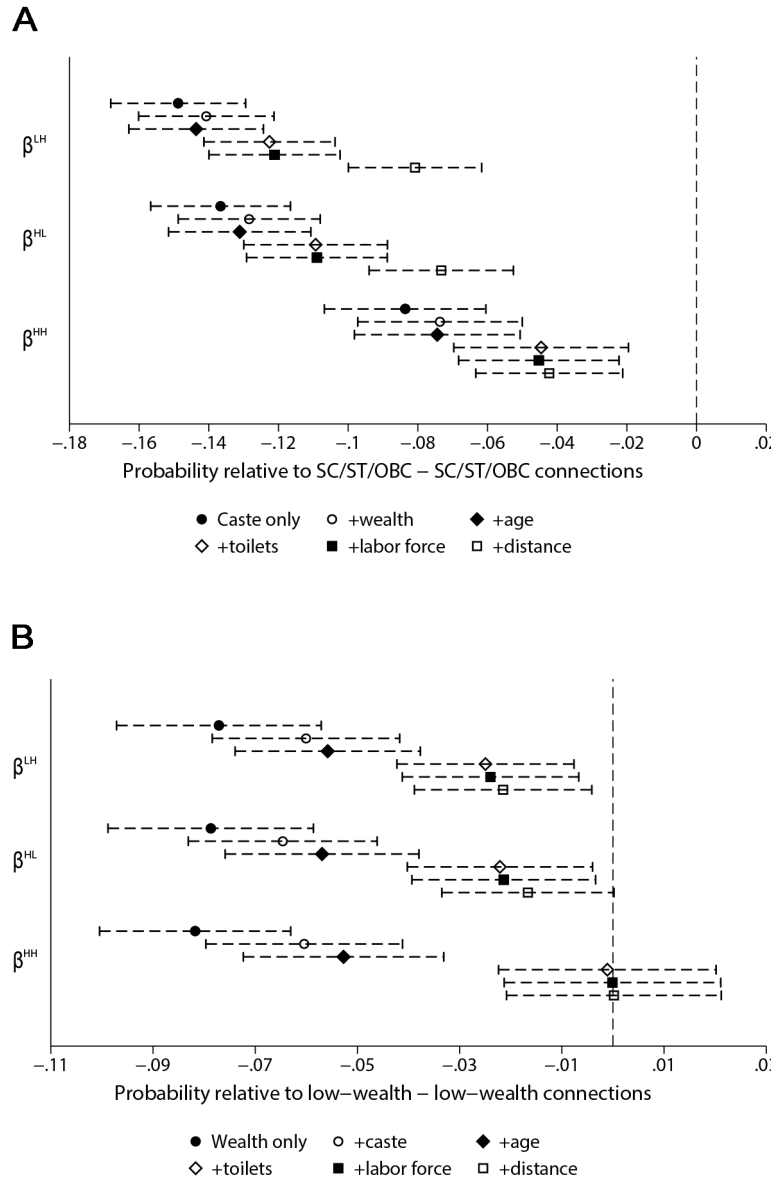


Figure 8. Mediation analysis of SES differences in connection probability in wave 1. *A*, Caste/tribe. *B*, Wealth. Panels *A* and *B* plot the coefficients $\hat{\beta}^{LH}$, $\hat{\beta}^{HL}$, and $\hat{\beta}^{HH}$ from the OLS regression as controls are sequentially added to the model. Wealth is a binary indicator equal to 1 if a household has a PCA asset score above the village median. Caste is a binary indicator equal to 1 if a household head is SC/ST/OBC. Age is mother's age in years. Toilets is a binary indicator of household toilet ownership. Labor force is a binary indicator of mother's labor force participation. Distance is distance to other mother in meters (included quadratically).

Figure 8*B* shows the same mediation analysis for the wealth gradient, plotting probabilities relative to low-wealth-to-low-wealth connections. Controlling for caste/tribe and age reduces by roughly 2 percentage points the wealth difference in both within- and across-group connectedness. Labor force participation and toilet ownership, as with the caste/tribe gradient, can also explain some of the wealth difference. This lends weight to the argument that mobility plays a role in the size of one's network. Indeed, once toilet ownership is controlled for, there is no remaining within-group difference in the probability of connections between low- and high-wealth mothers. Distance is associated with little of the wealth gradient, likely due to a lower degree of segregation (233 meters for within-wealth connections vs. 294 meters for across-wealth connections).

IV. Discussion and Conclusion

The extreme isolation of young mothers in rural India that we document is worrying given existing evidence, from various contexts, that social isolation is associated with poor mental and physical health for women (Berkman et al. 2000; Cacioppo and Hawkley 2003; De Silva et al. 2007; Kohler, Behrman, and Watkins 2007; Fowler and Christakis 2008; Sawyer, Ayers, and Smith 2010; Smith and Postmes 2011) and with women more likely to be victims of domestic violence (Lanier and Maume 2009; Choi, Cheung, and Cheung 2012). Adverse effects of social isolation on mothers may have knock-on effects on their children (Sawyer, Ayers, and Smith 2010; Kingston and Tough 2014; Bennett et al. 2016). Much of the existing evidence on the effects of social isolation comes from high-income countries where the reasons for and consequences of isolation probably are substantially different from the context we study because of, for example, fewer restrictions on women's mobility, higher incomes and higher rates of women working outside of the home, and less restriction due to social structures such as the caste system. More evidence on the correlates of isolation for young women in contexts with highly restrictive gender norms and in high-poverty settings is useful to understand the costs borne by women and communities as a result of female isolation.

Within our own data, we can examine correlations between social networks and broader indicators of women's well-being. Figure 9*A* plots these associations for both an indicator of women's empowerment, as measured by an index summarizing 10 questions covering household decision-making and independence.[23] Figure 9*B* plots the same for symptoms of depression, as measured

[23] Five questions relate to who (within the family) decides what to do in different scenarios; e.g., "Who decides how much money is spent on food?" Five questions relate to independence; e.g., "Do you own any asset of value you could sell to make a needed payment?" We combine these using

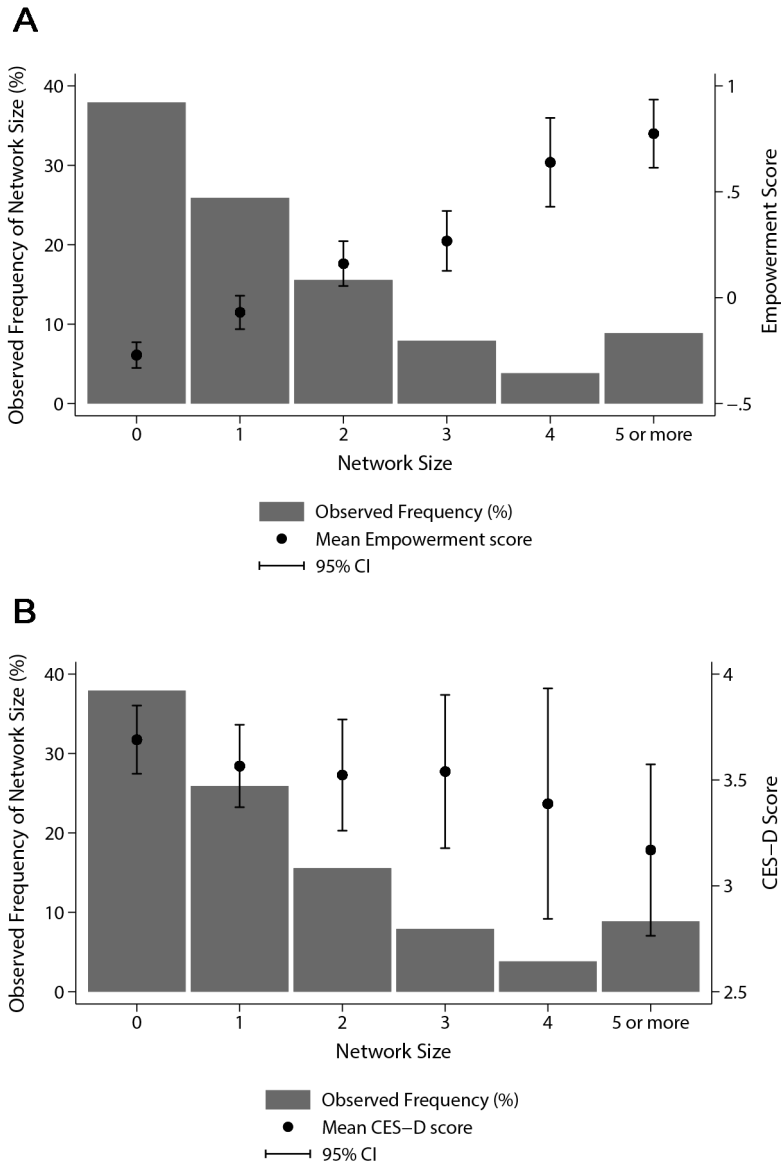


Figure 9. Correlations between network size and empowerment and symptoms of depression. *A*, Empowerment. *B*, Symptoms of depression.

by the 10-item version of the Center for Epidemiologic Studies Depression Scale (CES-D; Andresen et al. 1994). Figure 9*A* shows clearly that larger network sizes

a two-parameter IRT factor model to create a summary score with zero mean and unit variance. The index is coded such that higher values represent more empowerment.

are associated with women being more empowered. The empowerment index is scaled to have a zero mean and unit standard deviation in our sample. We find that while women who report having zero connections have an average empowerment score of –0.27, those who report having five or more connections have an average empowerment score of 0.77. Table A7, which reports the same results in a regression framework, confirms this very substantial correlation and shows that it remains similar in magnitude and significance once controlling for covariates. Figure 9*B* shows the correlation between network size and symptoms of depression, which has a mean of 3.6 and a standard deviation of 2.4 in our sample. This correlation is substantially weaker than that with empowerment, although there is nevertheless a statistically significant negative relationship whereby women who have larger networks report fewer symptoms of depression (also see table A7).

Given the very high degree of social isolation among young married women in rural India, it is important to understand more about the effect of governmental policies and large-scale programs on connectedness. Recent work has shown that women's educational programs can be successful at expanding women's social networks (Kandpal and Baylis 2019). Conversely, relocation programs for slum dwellers can shrink networks (Barnhardt, Field, and Pande 2017). However, little evidence exists about the effect of national programs, including employment programs such as the National Rural Employment Guarantee Act in India, that may indirectly expand or contract women's social networks. The Indian government has recently made huge investments in expanding access to private toilets through the Swachh Bharat Mission (Curtis 2019), and our results suggest that evaluations of this effort may want to consider the policy's unintended effects on female isolation.

We need to better understand the nature of the relationship between social isolation and wealth and amenities, because here we cannot establish causality. Further research should study how women's networks relate to those of men and how important each of these networks is for information dissemination, insurance, and other economic and social activities. With that understanding, we may start to see how economic growth may affect social networks, which can be crucial for individual well-being.

The analysis we have presented in this paper is descriptive, and thus we do not draw firm causal conclusions about the causes and the consequences of women's isolation, which can include negative effects on their well-being and on the development of their children, thereby deepening the intergenerational transmission of poverty and inequalities. However, we consider the extent of isolation we document, and its association with SES, to be a cause for concern and a motivator for future research on this topic.

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