Income-Based Homophily and Social Capital:
Experimental Evidence from Malawi*

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Abstract

I seek to understand the driving factors and downstream impacts of income-based homophily for low-SES female rural migrants in Malawi. I experimentally reduce the effort cost of inviting low-SES, high-SES, or a random mix of female migrants for a shared meal. I cross-randomize a voucher for a butcher to test if budget constraints drive demand for homophily or impact the benefits of economic connectedness. I find evidence suggesting that within-SES relationships are more-preferred under budget constraints than with budget slack, but with heterogeneity. The voucher induces the largest increases in invitations to high-SES women for credit-constrained women, and induces the largest increases in invitations to low-SES women among baseline lonely or depressed women. Exogenous linking with high-SES women leads to a 53% increase in business-operating, regardless of having the voucher. With the voucher, exogenous linking with high-SES women also leads to inclusion in high-SES networks and financial self-help group membership. Exogenous linking with low-SES women leads to an increase in perceived acceptance, especially among baseline lonely or depressed women, and these positive effects are amplified with the voucher. When participants select the SES of the women to invite, large downstream effects bear out across a host of outcomes, regardless of having the voucher. I draw three conclusions from these results: (1) budget constraints play a central role in driving the formation and persistence of income-based homophily in social networks; (2) there is heterogeneity in the types of benefits that individuals derive from cross-SES versus within-SES, generating heterogeneity in demand for homophily; and (3) there is heterogeneity in match-quality of cross- and within-SES links, implying that selection into meeting opportunities plays an important role in the materialization of social capital benefits.

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1 Introduction

Homophily, or the tendency for people to be socially connected with other people who are similar to them, is a robust feature of social networks. Homophily is descriptively documented across many settings and characteristics, including income, and has important implications for the persistence of differences in economic outcomes across groups (Verbrugge, 1977; McPherson et al., 2001; Jackson, Forthcoming). Homophily also has implications for social and cultural cohesion if, as proposed by the "inter-group contact theory" and demonstrated in some settings empirically, exposure to different-type people is an important mechanism for reducing inter-group prejudice (Allport, 1954; Rao, 2019). Despite the widespread prevalence of homophily and its economic relevance, we know very little about *why* social networks become and remain homophilic. Furthermore, while descriptive evidence points to economic connectedness (or, having many cross-social-class links) as potentially the singular most important correlate of economic mobility (Chetty et al., 2022a), we have limited *causal* evidence of the impact of economic connectedness per se on economic or social outcomes, nor evidence on how to induce economic connectedness.

In this project, I use a social networks experiment in Malawi that exogenously provided women with social linking opportunities within and across social class to understand why income-based homophily arises and persists in social networks. I find that the high prices of valuable socialization activities plays a central role in driving the formation and persistence of income-based homophily in social networks, implying that income-based homophily is self-reinforcing. However, there is heterogeneity in the types of benefits that individuals derive from cross-SES versus within-SES relationships, generating heterogeneity in demand for homophily. Using the downstream outcomes of the experiment, I provide the first causal evidence of the economic benefits of economic connectedness. I also provide novel evidence on the positive benefits of homophilic links, which *do not* materialize from non-homophilic links.

In the experiment, I help young low-SES female migrants initiate meal-sharing with other female migrants, a common way to engage socially. For one group, the women available to send invitations to are all low-SES, implying that the experiment generates exogenous within-SES links for these women. For another group, the women available to send invitations to are all high-SES, implying that the experiment generates exogenous cross-SES links for this second group of women. And for a final group, the women available to send invitations to are a random mix of both high-SES and low-SES women, implying that the experiment generates exogenous links in which women can select into the specific match type. I randomize a voucher for a butcher across these three groups, which reduces the price of a high-status meal to the same price as a lower-status meal.

I find evidence that the social frictions and effort costs associated with initiating social engagements are prohibitively high – 81% of women sent an invitation through the intervention, 99% of which were to women *outside* the baseline network. The rates of invitation-sending did not vary across any of the treatment arms, suggesting that the effort costs of initiating social

engagement with high-SES and low-SES women may not be differentiable. However, when women could invite from a list of both high-SES and low-SES women, they were more likely to send an invitation to a high-SES woman. This increase in invitations to high-SES women is driven by women who were at baseline more credit-constrained. Conversely, women who were either lonely or depressed at baseline were more likely to send an invitation to low-SES women with the voucher.

I present a novel model of social network formation under budget constraints that rationalizes these finding. The predictions that the model generates offer two important insights into homophily. First, the high prices of high-value social goods act as a key driver of homophily, implying that income-based homophily – a case of homophily in which, by definition, one group is unable to afford high-value social goods – is self-reinforcing. Second, homophilic and non-homophilic relationships impart different benefits, implying that there is heterogeneity in demand for homophily, and that selection into high-quality matches plays an important role in maximizing the potential benefits of relationships.

In the model, social relationships impart benefits in two ways. First, people derive direct utility from relationships, which captures the immediate utility somebody experiences from socializing (companionship, mental health benefits, etc.). Second, there is a financial return on social relationships. This allows people to derive instrumental utility from relationships: the utility from the consumption that individuals can afford because of the financial return on their relationships. I assume that the *direct* utility that individuals experience from homophilic relationships is diminishing in social activity slower than non-homophilic relationships. This assumption generates the predicton that people with low baseline levels of direct socialization utility – or baseline lonely or depressed women – should be the most likely to put high-value social inputs into *homophilic* (low-SES) links. Second, I assume that the *instrumental* utility that individuals experience from non-homophilic relationships is diminishing in social activity slower than homophilic relationships. This assumption generates the predicton that people with low baseline levels of financial return from socialization – or baseline credit-constrained women – should be the most likely to put high-value social inputs into *non-homophilic* (high-SES) links. Finally, I assume that the second force is more powerful than the first, so that the *total* utility that individuals experience from non-homophilic relationships is diminishing in social activity slower than homophilic relationships. This assumption implies that, on average, when women can afford high-value social goods, cross-SES links become more valuable relative to within-SES links, so effort into cross-SES links also increases relative to effort into within-SES links.

I then use the experiment to study the downstream impacts of social connectivity and economic connectedness. After one month, I find that the opportunity for a low-SES woman to send an invitation to a high-SES woman leads to a 53% increase in the probability of earning income through the sale of goods or services (for example, selling vegetables in the market or prepared foods on the roadside). In a setting where most people rely on subsistence agriculture, selling

goods and services represents an important source of liquidity outside of the harvest season, and is more lucrative than daily paid labor (the other primary income-earning activity outside of agriculture and sales). When low-SES women had the opportunity to send an invitation to a high-SES woman *and* had the voucher, they were able to gain access to high-SES network groups. Membership in financial self-help groups (which are dominated by high-SES women) increases by 12%, and their networks are more likely to be majority or *entirely* higher-income women. When low-SES women had the opportunity to send an invitation to another low-SES woman, feelings of perceived acceptance in the village increases by 0.12 SD in the group who also had the voucher. Among low-SES women who were lonely or depressed at baseline, the opportunity to invite another low-SES woman leads to a 0.25 SD increase in perceived acceptance, regardless of having the voucher. Finally, among women who had the opportunity to invite both low- and high-SES women, larger and *more varied* benefits materialize: increases in earning income through sales, savings, consumption, and perceived acceptance.

This paper contributes to four bodies of work in economics. First, I contribute to the social networks literature by providing evidence about how social networks form and why they persistently feature homophily. While there is an extensive literature that uses the social network structure as an intermediary for the diffusion of information and technological interventions (Akram et al., 2025; Banerjee et al., 2019, 2024a; Beaman, 2012; Beaman and Magruder, 2012; Beaman et al., 2021; Bikhchandani et al., 2024; Breza and Chandrasekhar, 2019; Chandrasekhar et al., 2022; Kondylis et al., 2023), there are few papers to date analyzing how social networks themselves change in response to interventions. Notable exceptions include Banerjee et al. (2024b), which analyzes the way in which the entry of formal financial institutions disrupts existing social linkages in Indian villages and Schechter and Vasudevan (2024), which finds that linking women in India via social groups increases friendships and the exchange of taboo information.

I present a novel theoretical model of social network formation under budget constraints, where the high prices of high-value social goods act as a key driver of income-based homophily. I show that the model predictions bear out empirically through an experiment with randomized social linking by facilitated invitation-sending for a shared meal. To my knowledge, this is the first causal evidence to date identifying the drivers of homophily in social networks. I find that demand for homophily *is* an important driver of homophily, but with two important caveats. First, people do have a preference for meeting with homophilic links, but there are no differences in the probabilities of linking with cross-SES or within-SES women conditional on *exogenous* meetings. Second, there is no evidence of biased preferences – either at the meeting or linking stage – when participants have the voucher. Together, this evidence indicates that the high price of high-value social goods is a key driver of income-based homophily by preventing cross-SES meetings from happening in the first place.

Second, I contribute to a growing body of work documenting the positive relationship between economic connectedness and economic outcomes, including economic mobility (Chetty et al.,

2022a), entrepreneurial activity (Patel and Wolfe, 2024), and better population health (Linde and Egede, 2023). A related body of work causally identifies the effects of distinct but related phenomena, such as the peer effects of higher-income roommates (Sacerdote, 2011), the effect of peers' employment status (Laschever, 2013), the effects of moving from low-income to high-income neighborhoods (Bergman et al., 2024a; Chetty et al., 2016; Ludwig et al., 2013), and the effects of being assigned to classrooms with a higher proportion of high-income students (Mallah, 2025). To my knowledge, this paper provides the first causal evidence of the impact of economic connectedness outside of an educational context (where mechanisms at play, such as classroom resources, may not replicate to other settings); the first experimental evidence of the impact of economic connectedness; the first evidence of the impact of economic connectedness in a low- or middle-income country;[1] and the first test of an intervention that specifically engenders economic connectedness.[2] Furthermore, my study design allows me to interrogate heterogeneity by "match quality" in the benefits of economic connectedness. While other studies can evaluate results heterogeneously by a variety of baseline characteristics, my experiment is unique in its ability to test heterogeneity by *selection into matches*. This allows me to test if people understand match quality and are able to select high-quality matches, and to evaluate heterogeneity by match quality *even if* the determinants of match quality are unobservable in the data. My results imply that selection into high-quality matches may contribute to the benefits of economic connectedness in descriptive data.

Third, I contribute to the literature on mental health in developing countries. While a growing literature shows mental health disorders and loneliness are highly prevalent among low-income people (Banerjee et al. (2023); Ridley et al. (2020)), there is limited evidence documenting causal pathways, and there is room for finding novel cost-effective mitigation strategies.[3] This study provides evidence that the social isolation that individuals experience as a result of their *relative* income status is a mechanism underlying mental-health poverty traps, a causal pathway that has not received much empirical attention to date.[4] I document novel patterns

[1]Much of the evidence documenting the effects of economic connectedness, or even establishing the prevalence of income-based homophily, is from the United States (Chetty et al., 2022a,b; Bergman et al., 2024b; Nilforoshan et al., 2023; Yabe et al., 2023).

[2]The causal evidence of economic connectedness to date either bundles economic connectedness with other goods, as in the "Moving to Opportunity" literature where "better" neighborhoods are a bundled good that includes economic connectedness (Bergman et al., 2024a; Chetty et al., 2016; Ludwig et al., 2013); or analyzes the impacts of economic connectedness that happens through the randomization of peer groups, especially in educational contexts. In the peer groups literature, some people randomly have higher-income peers, and some randomly have lower-income peers. While this provides a source of variation through which to study the impact of high-income peers on low-income students, this is not an intervention that induces economic connectedness for everyone, and thereby not a relevant policy option for a social planner interested in increasing economic connectedness broadly.

[3]Many of the interventions with the largest positive effects on mental health are not cost-effective, such as cash transfers (see Haushofer and Salicath (2023) and Ridley et al. (2020) for a review). Interventions that are cost-effective and targeted directly at improving psychological well-being, such as psychotherapy and pharmacotherapy, improve mental health across a variety of low-income settings (Angeluci and Bennett, 2024; Bhat et al., 2022; Blattman et al., 2023; McKelway et al., 2023; Patel et al., 2007). However, these interventions explicitly treat mental health disorders and thereby risk low take-up or causing stigma (Smith, 2024; Ridley, 2025; Pescosolido, 2013).

[4]See Haushofer and Salicath (2023) for a review of the evidence on "scarcity" and stress mechanisms, which a multitude of causal studies evaluate but find inconclusive evidence for.

in the prevalence of loneliness,[5] causally identify social isolation from the in-group as a cause of perceived alienation, and elucidate the importance of "bonding capital" (having more or stronger in-group links) in generating feelings of community acceptance. Furthermore, I provide a practicable intervention that can reduce feelings of alienation among lonely and depressed women.

Fourth, I contribute to an old literature in development economics on demand for food and nutritional poverty traps by demonstrating that food serves as a *social input* as well as a health input or consumption good.[6] I provide evidence that consuming expensive calories can be a rational *investment decision* – rather than, or in addition to, being a luxury consumption good – with substantial economic returns through its role as a social input.

The paper proceeds as follows: Section 2 discusses the background and cultural context, Section 3 describes the experimental design, Section 4 presents a theoretical model of homophily, Section 5 presents first-stage results of the experiment (invitation-sending decisions), Section 6 present results on the downstream effects of social capital investments, and Section 7 concludes.

2 Background

I provide summary statistics and background information about my sample of low-income rural-to-rural female migrants in Malawi. This sample is triply disadvantaged with regards to social inclusion on the basis of their gender, migrant status, and income status.

2.1 Rural Migration

This project is set in Mchinji, a rural district in Central Malawi. While there is a large economics literature on rural-to-urban migration in low- and middle-income countries, the consequences of and trends in rural-to-rural migration has received less attention. Eighty-five percent of my sample moved across rural villages for marriage. My sample provides a convenient sample among whom to study social inclusion *precisely because* they face social exclusion *as women*. Furthermore, marriage migration is an exceedingly common phenomenon, especially for women. In seventy-one percent of societies worldwide, women move to the area where her husband and his kin live (Murdock (1967)).

The population in Mchinji District primarily belongs to two tribes. The predominant group

[5]The evidence on the prevalence of loneliness in low- and middle-income countries to date focuses on elderly populations. I provide estimates and correlates of loneliness rates among a younger population.

[6]The canonical nutritional poverty trap model theorizes that budget constraints prevent individuals from consuming adequate calories, but that inadequate caloric consumption prevents individuals from supplying labor and earning income, leaving the very poorest people stuck in a low-productivity equilibrium (Dasgupta and Ray, 1986). The nutritional poverty trap has been questioned on the basis that individuals consistently choose to spend excess income on more foods that are much more expensive per calorie, rather than cheap calorie-dense foods (Subramanian and Deaton, 1996; Jensen and Miller, 2008). This paradigm assumes that calories are the only dimension by which foods are an economic input. Dasgupta et al. (2023), which shows that beef bans in India lead to increases in iron-deficiency anemia, provides evidence that there are other dimensions of nutrition beyond calories that might enter into an individual's health investment decision when choosing foods.

is the Chewa, a traditionally matrilocal tribe (meaning, men move to women's villages at the time of marriage). The second most populous group in the area is the Ngoni, a traditionally patrilocal tribe (meaning, women move to men's villages at the time of marriage). However, these traditional kinship systems have been largely disrupted, and a significant portion of Chewa women move to their husband's village. Due to the diversity of kinship norms in the area, and their dynamic fluidity, it is not immediately obvious which other women are migrants. In the 2015 Malawi Demographic and Health Survey, 57% of women in Mchinji were in a different village than the one they grew up in. This is a fairly representative district in Malawi – 43% of the women in all other districts in Malawi were in a different village than the one they grew up in for the 2015 Malawi DHS survey, though with regional variation (Figure A.1). As kinship norms rapidly develop and change, there are no village- or tribal-level institutions to support women when they migrate, while centuries-old norms and societies exist to support Chewa men when they move to new villages for marriage (Kachapila, 2001).

While traditional kinship roles are important context to keep in mind, land ownership is now an important predictor of moving villages. In the 2015 Malawi DHS, 67% of women without any land or owned property moved villages, as compared to 39% of women who owned either land or property. Even controlling for region and tribe fixed effects, land ownership was associated with a 22 percentage point decrease in the probability of having moved villages (Table A.1).

2.2 Correlates of Social and Economic Inclusion

Measures of social inclusion include objective measures, such as membership in group activities and having many social links, and subjective measures, such as loneliness. I use access to credit as a measure of economic inclusion. Social and economic exclusion are highly correlated with one another, and with underlying person characteristics.

2.2.1 Defining Socio-Economic Status

I construct an index of socio-economic status. The SES index is the inverse-covariance-weighted index (Anderson, 2008) of the following variables: an indicator for having a high-quality roof material, an indicator for if the respondent lives in her own home,[7] acres of farmland owned, number of garden plots owned, and an index of business capital.[8] There are two main classes of income-generating assets in this region: farmland and a business. Land ownership serves as a proxy for farming assets, and I create a proxy for business capital based on the type of businesses that each woman's household engages in. I use the Anderson (2008) index because the households who engage in farming and business may be different, and Anderson (2008) down-weights correlated variables – thus, both the stock and the diversity of assets are rewarded

[7]Since many of the respondents were recent migrants, some did not live in their own home and were staying with a relative or other acquaintance while their home was under construction. In order to account for these cases, where income and roof material may be more likely to be discordant, I included a variable indicating if a respondent did not live in her own home.

[8]See Appendix Section **??** for a detailed description of how I constructed the business capital index.

in the index.

When I need to consider a binary version of socio-economic status, I split the SES index into two groups: high-SES, or the women in the top 20% of the SES index (quintiles drawn within geographic clusters); and low-SES, or the women in the bottom 80% of the SES index. Note that these women are *relatively* lower- and higher-income than one another, but are still all very poor on a global scale, and even within the context of Malawi. Only 20% of the high-SES women have had one member of the household complete secondary school, and on average eat fewer than three meals per day (Table A.2). That said, there are still stark differences between the high- and low-SES samples. High-SES women have almost double the landholdings that low-SES women have, and are almost twice as likely to have a household business (an important source of liquidity, especially after harvests are depleted).

When I need to consider the income of participant's network connections, I cannot use the SES index. Since participants have network connections who are outside the sample, I do not have the same rich set of data available for them. Furthermore, I cannot ask respondents to report this information about their network connections, because participans are unlikely to have precise information about their network connections' landholdings and business capital. However, it *is* likely that participants know the material of each of their network connections' roofs. Roof material is an observable household feature, and a salient proxy for income. Thus, when I analyze participants' connectedness to high- or low-SES people, I use the roof material of their network connections as a measure of income. While roof material is a more coarse proxy, and is not as good at identifying the highest-income individuals because 38% of the sample has a higher-quality (iron sheets) roof, it approximates the high- and low-SES samples fairly well (Table A.2).

Socio-economic status and the number of years that women have been in the village are both significantly correlated with social inclusion (Figure A.2) and economic inclusion (Figure A.3). As women get richer and have spent more time in the village, loneliness decreases, the number of friends a woman has increases, and the probability she belongs to a women's church group increases. Importantly, the probability that she belongs to a Village Savings and Loan Association (VSLA) *also* increases dramatically, with women in the top decile of socio-economic status being almost three times as likely to belong to VSLA compared with the bottom decile. VSLA is the most-preferred financial self-help group in this setting, and the most important source of credit, especially formal credit. These correlations bolster the assertion that this group of low-income migrant women is specifically marginalized with respect to social and economic inclusion.

2.2.2 Depression and Loneliness

Among the sample of low-income migrant women, 36% are likely depressed or lonely at baseline, with the larger portion of these women at risk of depression (27% depressed, and 14% lonely). Note that, although depression and loneliness are correlated, the correlation is quite weak

($\rho = .113$) and only 6% of the sample is both depressed and lonely.

Consistent with recent work documenting high levels of depression among the elderly in low- and middle-income countries (Banerjee et al., 2023), depression is starkly increasing in age – 23% of the youngest 10% of the sample are likely depressed (ages 18-20), whereas 36% of the oldest 10% of the sample are likely depressed (ages 42 to 69) (Figure A.4, left-side panel). Conversely, loneliness is most prevalent among the youngest generation – the prevalence of loneliness is 16% among 18-20 year-old women. Loneliness is steadily decreasing in age up until middle age (the least lonely cohort is women ages 37-41, where 9% are lonely). However, the oldest 10% of the sample – women ages 42 to 69 – are as lonely as the youngest generation, with 16% prevalence.

This evidence suggests that loneliness and depression, while correlated, are independent objects with distinct origins. Surprisingly, while there is a significant correlation between socio-economic status and loneliness, there is *no correlation* between socio-economic status and depression. However, there is a very strong correlation between low food consumption and *both* loneliness and depression. Consuming on average three meals a day (38% of the low-income sample) is associated with a 13 percentage point (42%) reduction in depression, and a 9 percentage point (46%) reduction in loneliness. Having consumed *any* meat in the past month (77% of the low-income sample) is associated with a 10 percentage point (28%) reduction in depression, and an 8 percentage point (46%) reduction in loneliness. Recall that the index of socio-economic status is constructed from variables indicating asset ownership (productive assets and home quality), rather than consumption.

I construct an index of how challenging it is for a participant to return to her home village – the price of transport, time that a trip home takes takes, and visits that the participant makes per year. This index is significantly correlated with both depression and loneliness (Figure A.4, right-side panel).

2.2.3 Baseline Networks

At baseline, participants have six network connections on average (mean = 6.2, median = 6, IQR=2). These networks are, on average, split equally between relatives and non-relatives. However, the relatives are most often from the husband's side of the family, and the non-relatives are most often people who the respondent met herself (not through her husband).

Baseline networks are homophilic with respect to income (using roof material as a proxy for income status). Figure 1 demonstrates village-level homophily by roof material across the twelve villages in my study. In every village, participants with iron sheets roofs are more likely to link with other people with iron sheets roofs than you would expect if they linked with people within the village at random; and in all but four villages, participants with thatched roofs are more likely to link with other people with thatched roofs than you would expect if they linked with people within the village at random.

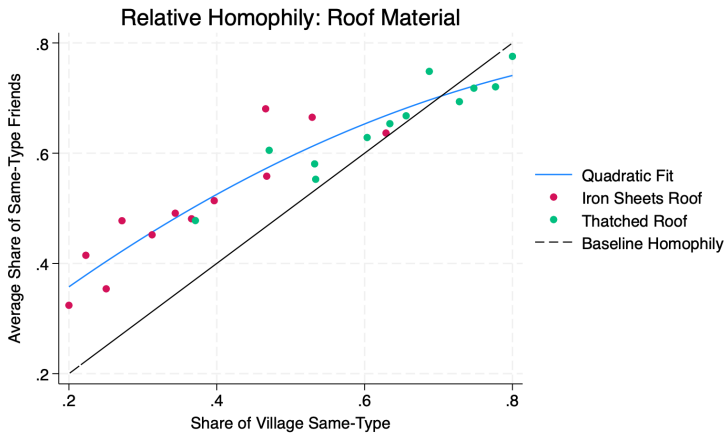


Figure 1: Income-Based Homophily

To elicit networks, enumerators asked participants to list each person with whom she ever engages with in a series of activities. The most common activity to engage with network links in is meal-sharing – on average, 61% of network links are listed as somebody who the participant hosted for a meal in the past year (median = 60%, IQR=37%), and 56% of network links are listed as somebody who the participant visited for a joint meal in the past year (median = 56%, IQR=42%).

2.3 Meal-Sharing

Meal-sharing is a common social activity. At baseline, 90% of respondents reported that they shared a meal with somebody outside their household in the previous week, with 68% of respondents both visiting somebody at least once and hosting somebody at least once in the past week. Participants report hosting others more often than visiting others, though both are common (they hosted 2.3 meals in the past week on average, and visited others for 1.6 meals in the past week on average). For shared meals that participants host and shared meals where they visit others, it is equally common to go after being invited and to initiate a shared meal without an invitation. Anecdotally, shared meals that happen without an invitation are a result of visiting a friend in her home while she is cooking.

Why is meal-sharing such a common activity? While *food*-sharing is a common method of risk-sharing, *meal*-sharing also encompasses sitting down together and eating with one another. Survey evidence suggests that this joint activity has benefits beyond the risk-sharing benefit of sharing food. In a sample of sixty-eight participants in rural Lilongwe (the district adjacent to Mchinji, where I conduct my experiment), I asked participants how personal a conversation could become across four settings: a shared meal, while working, while doing chores, and while at church. Both male and female participants overwhelming and consistently rated a shared meal as the setting where a conversation could become the most personal, regardless of if they imagined the shared meal to be with somebody who they typically share meals or with somebody with whom they know from working together (Table A.3).

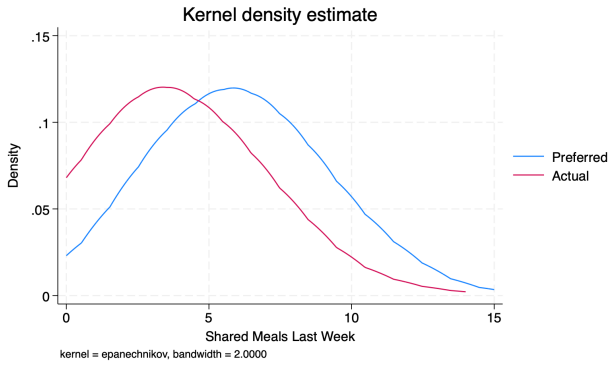


Figure 2: Preferred versus Actual Meal-Sharing

Despite the high prevalence of meal-sharing, 72% of respondents report that they would prefer to share more meals per week than they currently share. Women reported that they would prefer to share more meals than they did last week across the distribution of last week's meal-sharing (Figure 2). Sixty-five percent of respondents would prefer to host others more often, and similarly, 64% would prefer to visit others more often (47% would prefer to host *and* visit others for shared meals more often than they currently do). While the objective of this paper is not to decompose the forces underlying this gap, I propose two primary contributors: high costs of initiating social relationships, and information frictions.

High Costs of Initiating Relationships

I implemented vignettes to understand social norms around meal-sharing and the barriers that women face when sharing meals with other women in the village. At baseline, enumerators read participants a vignette about a hypothetical woman in the village named Grace who would visit a neighbor to eat a meal together. In the vignette, the age and occupation of Grace and her neighbor were randomized (the ages were 25 or 45, and the occupations were subsistence farmers who cultivated their own land, versus agricultural day-laborers). Enumerators asked participants what are the likely reasons that Grace visited her neighbor in hopes of sharing a meal. In the case where both Grace and her neighbor were agricultural day-laborers, 55% of respondents believed that Grace sought to share a meal out for the *food* (financial necessity or seeking out higher-quality food), rather than for the company. When the neighbor was a landholder and Grace was not a landholder, the percent of respondents who believed she was visiting in search for food rose by another 12 percentage points (there was no difference across the other conditions). Almost all of the remaining participants (43%) said that Grace sought to share a meal because she and the neighbor were existing friends. Only 12% and 11% of women believed that Grace sought to share a meal because she wanted to become friends with the neighbor, or because she simply enjoyed being in the company of others (respectively).

Enumerators then read participants another vignette about a woman named Martha who considered visiting her neighbor while she was cooking to share a meal, and considered inviting her to share a meal, but decided not to. Seventy-five percent of respondents listed monetary concerns as the primary issue likely holding Martha back from visiting her neighbor, such as fear

of burdening the neighbor financially, fear of appearing poor ("beggar stigma"), and fear of not having the monetary resources to reciprocate a shared meal. Respondents were split between financial and social concerns as the frictions holding Martha back from inviting her neighbor. The most common concerns were that Martha was worried the neighbor did not like her (28%), and that Martha did not have enough food to share (26%). Other common concerns, with 20% of respondents listing the following as primary concerns each, were that Martha was worried about being a burden on the neighbor's time, that Martha was afraid that people would gossip about it, and that Martha was worried that the neighbor would feel belittled (stigmatized for needing the food support).

Staggeringly, seventy-five percent of respondents reported that they believed that these women's concerns about meal-sharing were likely to be valid concerns. These vignettes suggest that women face a myriad of concerns about initiating meal-sharing relationships. Even when women are financially able to share meals, the fact that people share food both for companionship and to assist the needy leads to deep concerns about burdening others, stigmatizing others, or stigmatizing oneself.

A natural question is if these concerns are true, or if this is a society in a state of pluralistic ignorance. Next, I examine descriptive evidence of pluralistic ignorance. Experimental results point towards some degree of pluralistic ignorance, along with real and prohibitive effort costs of initiating relationships.

Information Frictions

Are these valid concerns, or are women pluralistically ignorant of their joint willingness – and even desire – to share more meals? To understand the role of misperceptions about *other's* willingness to share meals, I asked women three questions: What percent of villagers do you believe would accept an invitation for a shared meal from a hypothetical villager? What percent of women similar to you in the village do you believe would accept an invitation for a shared meal from a hypothetical villager? What percent of women similar to you in the village do you believe would accept an invitation for a shared meal *from you*? As the questions become more personal, women become increasingly pessimistic, with 42% of women believing that women in the village like her would be less likely to accept an invitation from herself than from a hypothetical villager.

On average, participants believe that 49.9% of women similar to her in the village would accept an invitation from her, and that 54.3% of villagers would accept an invitation from a general hypothetical villager. However, 97% of women report that they themselves *would* accept a hypothetical invitation from another villager. While this is likely an overestimate of the true acceptance rate, as a self-reported and hypothetical figure, I am able to estimate an actual acceptance rate using endline data in the Control group. My most conservative estimate of the true invitation acceptance rate is 80%, which is higher than 80% of participant's baseline estimated acceptance rate even in the most general case. This evidence indicates that there is a

significant information friction whereby women systematically and pluralistically underestimate underestimate others' willingness to share meals to share specifically with her, as well as others' general willingness to share meals with others.

3 Experimental Design

The RCT includes two intervention arms that each alleviate a friction to social interaction for women in rural Malawi: a meat price subsidy to reduce the price of a high-value social good, and an inviting service that resolves information frictions around socializing and reduces its effort cost. The service provided information about who in the village would like to share meals, which reduces uncertainty about the probability that an invitation will be rejected. Enumerators who provided the service sent invitations on the participants' behalf, which meant they did not have to bear the hassle costs of finding other women in the village to invite them, nor did they have to risk bearing the emotional cost of face-to-face rejection. I recruited a sample of 3,600 women who moved to the village after the age of 14 but no more than 20 years ago. I selected a 1,600-person subset of the sample for the intervention (henceforth, the Intervention Sample), selected randomly among women in the bottom 80% of an income index (proxy for lower-income) since high prices are more likely to be prohibitive for lower-income women. Of the women in the top 20% of the income index, I offered 500 the opportunity to be a Guest. Of the women who were in the bottom 80% of the income index, but were *not* selected for the Intervention Sample, I also offered 500 the opportunity to be a Guest.

Every participant had the opportunity to add their name to a list of women who were interested in sharing meals with other women in the village more often (Sharing List), knowing that at a later stage some women in the village would see the list and have the opportunity to invite people from the list. Almost every woman signed up for the list (99.6%), and almost all agreed to have their photo taken and displayed on the list so that women who did not know them by name could also send them an invitation (96.4%). The women who signed up for the Sharing List *and* were randomly selected to be a Guest had the opportunity to actually appear on the Sharing List.

The Intervention Sample was randomized into three groups:

1. Inviter Treatment (n=600) – This group viewed up to six names from the Sharing List and could invite up to five women on the list to share a meal (invitation delivered by enumerators).

2. Vouchers + Inviter Treatment (n=600) – Recipients received 4 USD (8% median monthly income) vouchers, redeemable at a local butcher, and the Inviter Treatment.

3. Control (n=400) – This group did not receive any intervention.

Within treatments 1 and 2, participants viewed one of three types of Sharing Lists: Low-SES Guest List (all women on the list were also in the bottom 80% on the income index), High-SES

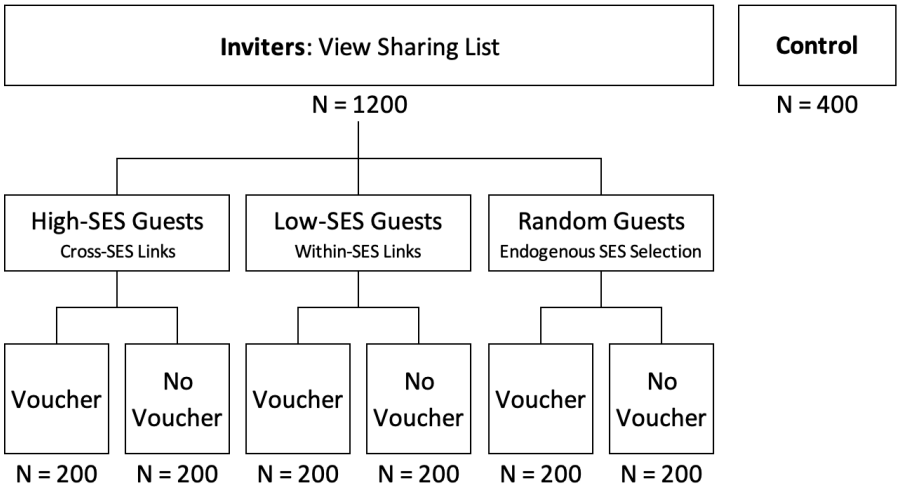


Figure 3: Intervention Sample – Treatment Groups

Guest List (all women on the list were in the top 20% on the income index), or the Random Guest List (names on the list were randomly selected across both the high-SES and low-SES subsamples). For each of these three groups, n=200 in treatment 1, and n=200 in treatment 2.

The SES index is constructed from variables collected in the listing survey, and has two advantages: because it is continuous, it allows me to draw precise quantiles of income within each village, so that I can control the portions of each village that is classified as High- or Low-SES;[9] and the Anderson (2008) weighting allows me to account for and reward uncorrelated ways of holding wealth within a single index.

Randomization was at the individual level, stratified by geographic-area clusters (clustering methodology described in Section 3.1) and quintile of the SES index. Randomization was stratified by geographic clusters to ensure that the density of the treatment arms did not differ spatially and create differential cultural shifts; and was stratified by the SES index since there are likely differences in income even among the people I classified as Low-SES, and the average income differences between the Inviters and Guests should be constant across treatment arms.

3.1 Cluster-level Program Saturation

I randomized the saturation of the Control group at a geographic cluster level. In a "high-saturation" cluster, 13% of women were randomized to Control. In a "low-saturation" cluster, 65% of women were randomized to Control. First, I defined geographic clusters. Then, I randomized each cluster to high or low saturation. Finally, I randomized individuals within clusters to treatment assignments, using the ratios as defined by their cluster-saturation-type.

I define geographic clusters using k-means clustering following Poll (2024). This unsupervised

[9]The treatment design requires precise portions of participants to be classified as High- and Low-SES – otherwise, we might conflate the effects of cross- versus within-SES relationships with the effects of interacting with more- or less-available people. Using a discrete measure such as roof material, which is a very salient and typical variable used as a proxy for income but varies dramatically across villages, would mean that the High-SES-cutoff would be at a different quantile of income in each village.

learning technique creates groups based on similarities in latitude and longitude. I specify that clusters must have at least 20 people in them, and should have 36 people per cluster on average. I chose 36 as the average size so that I would attain around 100 clusters, in order to ensure sufficient power to detect differences across Control respondents in high- and low-saturation areas. In order to ensure that this is a relevant geographic unit for social networks, I link the names of social network connections with people in my listing dataset and calculate how many relationships with someone in my sample are within the same cluster. I am able to link 7% of network links. Seventy percent of these links are within the same cluster, indicating that this is a network-relevant geographic unit. It is important to note that the relationships between respondents in my sample (the names who I can link) are not representative relationships. They are on average 4.4 minutes (58%) walking-distance closer than other relationships, and are 5 percentage points (16%) more likely to be friends rather than relatives. However, these relationships are likely good approximations for the types of relationships that my intervention created.

3.2 Data

I conducted three rounds of data collection: a Listing Survey with all 3600 participants (May 2024), a Treatment Allocation Survey with the Intervention Sample (July 2024), a Midline Survey with the Intervention Sample one month later (August 2024), and an Endline Survey with the full sample nine months later after the following harvest (May 2025).

3.2.1 Listing Survey

The Listing Survey was conducted in May 2024. In this survey, all participants were informed that some people would be selected for a project where they might receive a voucher and could invite other women to share a meal. We then explained to participants that, while we cannot say whether or not they will be selected for that program, they can have the opportunity to put their name on a list that indicates their interest in receiving an invitation for a shared meal from a neighbor. They were informed that the list will not be printed or physically distributed, so nobody would have the opportunity to show the list to others; and that the list would only be used if at least ten women from within their area signed up, so that they would only ever appear on the list if at least nine other women also appeared on the list. Enumerators then requested to take a photo of the participant in front of her house, to help others identify her when they see her name on the list (more than 99% of women signed up for the Sharing List, and more than 96% of women agreed to have their photo taken).

3.2.2 Treatment Allocation

The Treatment Allocation survey was conducted in July 2024. Women were randomized into treatment groups using a computer program after the Listing Survey. Women in the Intervention Sample all participated in the Treatment Allocation survey, in which they were informed of

their treatment status. Women were informed if they were recipients of the Voucher treatment. Then, women in the Inviter treatment saw a list of up to six names and photos and received the opportunity to send invitations to up to five women on the list. Finally, all women received instruction about how to fill out the food diary for the next two weeks.

Guest List Construction

Guests were randomly allocated to Inviters. First I randomized an order among Inviters for which to allocate Guests. One at a time in the pre-assigned order, I randomly selected one Guest (among those eligible to appear on that specific Inviter's list) to appear on that Inviter's list. A Guest was eligible to appear for a specific Inviter if she conformed to the Inviter's treatment (for example, a high-SES woman could not appear on the list of an Inviter randomized to see only low-SES Guest names), lived within 800 meters of the Inviter, and had not already appeared on ten lists.[10]

3.2.3 Follow-up Surveys

The Midline survey was conducted in August 2024. The Endline survey was conducted in May 2025.

3.2.4 Food Diaries

Intervention Sample participants were instructed to fill out a pen-and-paper food diary, where they marked from a list of food options what they consumed each day over the course of two weeks. They were also instructed to mark if each meal was a shared meal.

4 Model of Homophily Under Budget Constraints

I model the socialization actions that individuals will choose to take with other people, adapting the model of social network changes from Banerjee et al. (2024b) (henceforth BBCDJK). My model contributes to our understanding of homophily by demonstrating two phenomena: (1) there are different advantages to the kinds of benefits individuals can derive from more- and less-homophilic relationships, implying that we should expect to see heterogeneity in demand for homophily by "match type"; and (2) without financial investments, non-homophilic links are relatively less valuable compared to homophilic links, implying that people have a stronger preference for homophily under binding budget constraints than with budget slack.

[10]There were X participants who were randomized into the Intervention Sample but who attrited from the Treatment Allocation Survey. These participants were randomly replaced using women in the Control group who were not selected for the Intervention Sample who lived in the same geographic cluster as the attriter. In all but X cases I also was able to randomly select a woman from the same wealth quintile, to hold strata constant. X of these women were Inviters. Because the names from the Sharing List that each Inviter saw was dependent on *other* Inviters' Sharing Lists, I did not reconstruct the Sharing List for these replacement households. Note that this means that , for replacement households, the Guests available for them to invite were not necessarily within 800 meters.

We will consider two ways in which individuals get utility from social relationships. First, individuals get utility from socialization itself (for example, the mental health benefits of friendship) which we refer to as "direct utility". Individuals may invest in social relationships purely to experience utility from social connection. Secondly, social network connections have a financial return. Individuals do not experience utility from the money itself, but the extra income can then be used to consume goods and services from which individuals derive utility. We refer to the utility of the consumption that individuals can afford because of the financial return on socialization as the "instrumental utility" of social relationships. Individuals may invest in social relationships in the hopes of a financial return.

4.1 Model Set-up

There are $j \in \{1, 2, ...J\}$ individuals in a community and $\theta \in \{\Theta\}$ denotes social types. For simplicity, we will consider two social types: θ_{LSES}, low-SES individuals, and θ_{HSES}, high-SES individuals. We will model the socialization activities that an individual i decides to engage in with person j, where $\theta_i = \theta_{LSES}$, and $\theta_j \in \{\theta_{LSES}, \theta_{HSES}\}$.

Let $a \in \{\mathscr{A}\}$ be socialization actions that an individual can take, so that $a_{ij} \in \{0, 1\}$ indicates if i takes socialization action a with person j. Each action has a positive "value-weight" w^a – for example, more thoughtful or enjoyable socialization activities have higher weights, and more dull or impersonal socialization activities have lower weights. Value-weights are invariable across people and represent a socially agreed valuation of activities, rather than individual utility from socialization activities. Each action has a price p^a, which is also invariable across people since it is set by the market. Each action bears an effort cost $c^a_{\theta_i\theta_j}$, which we allow to vary by types θ_i and θ_j. Let $cov(p^a, c^a_{\theta_i\theta_j}) = 0$, but $cov(w^a, p^a) > 0$ and $cov(w^a, c^a_{\theta_i\theta_j}) > 0$. In other words, price and effort costs are not correlated, but higher-effort and higher-price activities *are* given more value-weights. Since w^a represents a socially-agreed valuation of activities, we assume that value weights are slow to adjust to changes in the prices or effort costs of activities. In other words, w^a will not change in response to temporary or individually-targeted price or effort shocks. Let $w_{ij} \equiv \sum_{a\in\mathscr{A}} w^a a_{ij}$ be the total value of socialization actions that i takes with j.

Following BBCDJK, each relationship has direct utility $v_{\theta_i\theta_j} + \epsilon^v_{ij}$, where $v_{\theta_i\theta_j}$ is the base direct utility that a θ_i person gets from taking socialization actions with a θ_j person, and ϵ^v_{ij} is an indiosyncratic noise term distributed according to an atomless distribution F_v. I extend BBCDJK to allow socialization actions to also have a financial return $y_{\theta_i\theta_j} + \epsilon^y_{ij}$, where $y_{\theta_i\theta_j}$ is the base financial return that a θ_i person gets from taking socialization actions with a θ_j person, and ϵ^y_{ij} is an idiosyncratic noise term distributed according to an atomless distribution F_y. Different from BBCDJK, I allow $v_{\theta_i\theta_j}(w_{ij})$ and $y_{\theta_i\theta_j}(w_{ij})$ to depend on w_{ij}. $E^+[v]$ represents the expected direct utility of engaging in socialization actions a_{ij}, conditional on taking those actions, and $E^+[y]$ represents the expected financial return of engaging in socialization actions

a_{ij}, conditional on taking those actions.

$$E^+[v] \equiv E[v + \epsilon^v_{ij} | \epsilon^v_{ij} > -v] = v + \frac{\int_{-v}^{\infty} \epsilon^v_{ij} dF_v}{\int_{-v}^{\infty} dF_v}$$

.

$$E^+[y] \equiv E[y + \epsilon^y_{ij} | \epsilon^y_{ij} > -y] = y + \frac{\int_{-y}^{\infty} \epsilon^y_{ij} dF_y}{\int_{-y}^{\infty} dF_y}$$

.

Note that $E^+[v_{ij}]$ and $E^+[y_{ij}]$ both depend on w_{ij} – and, implicitly through that dependence, they also depend on a_{ij} – but ϵ^v_{ij} and ϵ^y_{ij} are independent of w_{ij} and a_{ij}. I assume that individuals will only take a set of socialization actions if *both* i and j agree to them, and either party will only agree to that set of actions if they will not lose utility or money by taking those actions. Then, the probability that i takes actions ${a_{ij}}_{j \neq i, a \in \mathscr{A}}$ is:

$$P_{ij} \equiv (1 - F_v(-v_{ij}))(1 - F_y(-y_{ij}))(1 - F_v(-v_{ji}))(1 - F_y(-y_{ji}))$$

Let $\bar{v_i}(n_i)$ be the direct utility that i gets from her pre-existing social network n_i, and $\bar{y_i}(n_i, \cdot)$ be i's pre-existing income, which depends on the pre-existing network. Then $V_i(a_{ij})$ is individual i's direct utility of socialization and $Y_i(a_{ij})$ is i's income after taking socialization actions a_{ij}:

$$V_i(a_{ij}) \equiv \bar{v_i}(n_i) + \sum_{j \neq i} E^+[v_{ij}(w_{ij})] \cdot P_{ij} - \sum_{j \neq i} \sum_{a \in \mathscr{A}} c^a_{ij} a_{ij}$$
$$Y_i(a_{ij}) \equiv \bar{y_i}(n_i, \cdot) + \sum_{j \neq i} E^+[y_{ij}(w_{ij})] \cdot P_{ij}$$

Agents choose Z_i, a consumption good, and actions ${a_{ij}}_{j \neq i, a \in \mathscr{A}}$ to solve:

$$\max_{Z_i, {a_{ij}}_{j \neq i, a \in \mathscr{A}}} U_i\Big(V_i(a_{ij}), Z_i\Big)$$

$$\text{s.t. } Y_i(a_{ij}) \geq Z_i + \sum_{j \neq i} \sum_{a \in \mathscr{A}} p^a \cdot a_{ij}$$

where U_i is concave in $V_i(a_{ij})$ and Z_i, $V_i(a_{ij})$ and Z_i are additively separable in U_i, and $\frac{\partial U_i}{\partial Z_i}$ is independent of $\bar{v_i}(n_i)$. Note that $\lambda = \frac{\partial U_i}{\partial Z_i}$ represents the marginal utility of consumption. Then $\lambda E^+[y_{ij}(w_{ij})]P_{ij}$ is the expected instrumental utility of taking socialization actions with j, $E^+[v_{ij}(w_{ij})]P_{ij}$ is the expected direct utility of taking socialization actions with j, and $\big(E^+[v_{ij}(w_{ij})] + \lambda E^+[y_{ij}(w_{ij})]\big)P_{ij}$ is the total utility of taking socialization actions with j.

4.2 Homophily

Our objective is to model the price-sensitivity of i in the socialization actions they choose to take with j, across more and less homophilic links and across the action-value domain. Note that $-\frac{\partial w_{ij}}{\partial p^a}$ is the elasticity of action-value with respect to the price of action a, and $\frac{\partial}{\partial w_{ij}}\big(-\frac{\partial w_{ij}}{\partial p^a}\big)$

is the rate of change in the elasticity of action-value with respect to the price of action a as action-value is increasing.

PROPOSITION 1: *Let* $\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{ij}^2} > \frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{ij}^2}$ *(the marginal instrumental utility from socialization is diminishing faster for homophilic links than for non-homophilic links). Then, all else equal* $\frac{\partial}{\partial w_{\theta_i\theta_{HSES}}}\big(-\frac{\partial w_{\theta_i\theta_{HSES}}}{\partial p^a}\big) - \frac{\partial}{\partial w_{\theta_i\theta_{LSES}}}\big(-\frac{\partial w_{\theta_i\theta_{LSES}}}{\partial p^a}\big)$ *is largest for people with low* $\bar{y}_i(n_i,\cdot)$.[11]

See Appendix Section C for a proof.

The instrumental utility returns to *non-homophilic links*, relative to homophilic links, is larger for higher-value actions than for lower-value actions. Because of the concavity of U_i in Z_i, people with low initial income will have the *largest* marginal instrumental value of socialization. Consequently, they will be *most* likely to increase the total value of socialization actions with θ_{HSES} individuals in response to changes in the price of high-value social actions.

PROPOSITION 2: *Let* $\frac{\partial^2 v_{\theta_i\theta_{HSES}}}{\partial w_{ij}^2} < \frac{\partial^2 v_{\theta_i\theta_{LSES}}}{\partial w_{ij}^2}$ *(the marginal direct utility from socialization is diminishing faster for non-homophilic links than for homophilic links). Then, all else equal* $\frac{\partial}{\partial w_{\theta_i\theta_{HSES}}}\big(-\frac{\partial w_{\theta_i\theta_{HSES}}}{\partial p^a}\big) - \frac{\partial}{\partial w_{\theta_i\theta_{LSES}}}\big(-\frac{\partial w_{\theta_i\theta_{LSES}}}{\partial p^a}\big)$ *is smallest for people with low* $\bar{v}_i(n_i)$.[12]

See Appendix Section C for a proof.

The direct utility returns to *homophilic links*, relative to non-homophilic links, is larger for higher-value actions than for lower-value actions. Because of the concavity of U_i in $V_i(a_{ij})$, people with low initial direct utility from their pre-existing network will have the *largest* marginal direct value of socialization. Consequently, they will be *least* likely to increase the total value of socialization actions with θ_{HSES} individuals in response to changes in the price of high-value social actions.

PROPOSITION 3: *Let* $\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{ij}^2} - \frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{ij}^2} > \frac{\partial^2 v_{\theta_i\theta_{LSES}}}{\partial w_{ij}^2} - \frac{\partial^2 v_{\theta_i\theta_{HSES}}}{\partial w_{ij}^2}$ *(the inequality expressed Proposition 2 is greater than the inequality expressed Proposition 1), so that* $\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{ij}^2} + \frac{\partial^2 v_{\theta_i\theta_{HSES}}}{\partial w_{ij}^2} > \frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{ij}^2} + \frac{\partial^2 v_{\theta_i\theta_{LSES}}}{\partial w_{ij}^2}$ *(the marginal utility of socialization is diminishing faster for homophilic links than for non-homophilic links). Then, all else equal,* $\frac{\partial}{\partial w_{\theta_i\theta_{HSES}}}\big(-\frac{\partial w_{\theta_i\theta_{HSES}}}{\partial p^a}\big) > \frac{\partial}{\partial w_{\theta_i\theta_{LSES}}}\big(-\frac{\partial w_{\theta_i\theta_{LSES}}}{\partial p^a}\big)$.

See Appendix Section C for a proof.

The total utility returns to *non-homophilic links*, relative to homophilic links, are increasing in the value of the socialization actions. In other words, socialization with non-homophilic links is relatively more sensitive (compared to homophilic links) to the price of higher-value socialization actions than the price of lower-value socialization actions.

[11] Empirically, I find that, among Inviters who only see the names of High-SES Guests, the voucher leads to an increase in business capital, VSLA, and the percent of the social network with a durable roof. The voucher has null treatment effects across all of these variables among Inviters who only see the names of Low-SES Guests. See Section 6 for a full discussion.

[12] Empirically, I find that, among Inviters who only see the names of Low-SES Guests, the voucher leads to an increase in perceived acceptance. The voucher has null treatment effects across these variables among Inviters who only see the names of High-SES Guests. See Section 6 for a full discussion.

4.3 Conceptualizing the Intervention

I define three specific socialization actions that an individual can take: $S \in \{\mathscr{A}\}$ is sending an invitation for a shared meal, with $w^S > 0$, $c_{ij}^S > 0$, and $p^S = 0$; $SH \in \{\mathscr{A}\}$ is sharing a meal, with $w^{SH} > 0$, $c_{ij}^S \approx 0$, and $p^{SH} > 0$; and $M \in \{\mathscr{A}\}$ is serving meat in a shared meal, with $w^M > 0$, $c_{ij}^M \approx 0$, and $p^M > 0$. I assume that i will only send an invitation if she is willing to share a meal. Then i will send an invitation to j if:

$$\begin{aligned} & c_{ij}^S + \lambda p^{SH} \\ & \leq (w^S + w^{SH})\Big(E^+\Big[\frac{\partial v_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}}\Big] + \lambda E^+\Big[\frac{\partial y_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}}\Big]\Big)P_{ij} \end{aligned}$$

Furthermore, i will send an invitation to j *and* serve meat in that shared meal if:

$$\begin{aligned} & c_{ij}^S + \lambda p^{SH} + \lambda p^M \\ & \leq (w^S + w^{SH} + w^M)\Big(E^+\Big[\frac{\partial v_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}+w^M}\Big] + \lambda E^+\Big[\frac{\partial y_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}+w^M}\Big]\Big)P_{ij} \end{aligned}$$

Inviter treatment: The Inviter treatment reduces the effort cost of sending an invitation c_{ij}^S by ωc_{ij}^S , $\forall j \in \{\text{Sharing List}\}$, with $\omega \in (0, 1]$. Inviters will send an invitation to a woman j on the Sharing List if:

$$\begin{aligned} & c_{ij}^S(1-\omega) + \lambda p^{SH} \\ & \leq (w^S + w^{SH})\Big(E^+\Big[\frac{\partial v_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}}\Big] + \lambda E^+\Big[\frac{\partial y_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}}\Big]\Big)P_{ij} \end{aligned}$$

Without the voucher, i can choose to send an invitation to j *and* serve meat in that shared meal if:

$$\begin{aligned} & c_{ij}^S(1-\omega) + \lambda p^{SH} + \lambda p^M \\ & \leq (w^S + w^{SH} + w^M)\Big(E^+\Big[\frac{\partial v_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}+w^M}\Big] + \lambda E^+\Big[\frac{\partial y_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}+w^M}\Big]\Big)P_{ij} \end{aligned}$$

Voucher: The voucher reduces the price of serving meat in a shared meal so that $p^M = 0$. An Inviter with the voucher can send invitations according to the rule above, and choose not to share meat (if, for example, she prefers to consume it herself or with pre-existing friends). However, she now has the option to send an invitation to a woman j on the Sharing List if:

$$\begin{aligned} & c_{ij}^S(1-\omega) + \lambda p^{SH} \\ & \leq (w^S + w^{SH} + w^M)\Big(E^+\Big[\frac{\partial v_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}+w^M}\Big] + \lambda E^+\Big[\frac{\partial y_{ij}}{w_{ij}}\Big|_{w_{ij}=w^S+w^{SH}+w^M}\Big]\Big)P_{ij} \end{aligned}$$

Note that she now experiences the benefits of serving meat in a shared meal, without paying

the additional cost.

Predictions

1. The Inviter treatment will lead to an increase in invitations towards women on the Sharing List if:
   - $c^S_{\theta_i\theta_j}$ is sufficiently low so that the ω effort-cost-subsidy brings the cost of sending an invitation below the threshold
   - $c^S_{\theta_i\theta_j}$ is sufficiently high so that invitation-sending is restrictively burdensome *without* the ω effort-cost-subsidy
2. The Voucher will lead to an increase in invitations to High-SES women in the Inviter group with the Random-SES Guest List
   - The voucher allows her to evaluate benefits at a higher level of w_{ij}
   - By Proposition 3, this should lead to an increase in the value of High-SES socialization relative to the value of Low-SES socialization, compared to their relative valuations at a lower level of w_{ij}.
3. In the Inviter group with the Random Guest List, the Voucher will lead to the largest increase in invitations to High-SES women among women who derive low levels of income from their existing network.
   - This follows from Proposition 2
   - As a proxy, we will use women who are credit constrained at baseline.
4. In the Inviter group with the Random Guest List, the Voucher will lead to the smallest increase in invitations to High-SES women (and may even lead to an increase in invitations to Low-SES women) among women who derive low levels of direct utility from their existing network.
   - This follows from Proposition 1
   - As a proxy, we will use women who are lonely at baseline.

5 Results: First Stage

5.1 Invitation Sending Across Treatment Sub-Groups

I analyze first-stage results – or invitation-sending decisions that participants made in the Treatment Allocation Survey – using the Inviter sample only. Eighty-one percent of Inviters invited at least one Guest, and the rate of inviting *anybody* is non-differentiable across treatment arms (Figure 4). Inviters invited 1.4 Guests on average (1.8 Invitees on average among Inviters who invited at least one Guest), with the Inviters in with the Low-SES Guest List inviting

slightly fewer women (Figure 4). The vast majority of these invitations were to women who were not in participants' baseline networks, indicating that effort costs of socializing are prohibitively high, yet easy to overcome with a simple intervention. Furthermore, I cannot rule out that $c^S_{\theta_{LSES}\theta_{HSES}} = c^S_{\theta_{LSES}\theta_{LSES}}$, or that there are no differences in the effort cost that a low-SES woman bears in sending an invitation to a low-SES versus a high-SES woman.

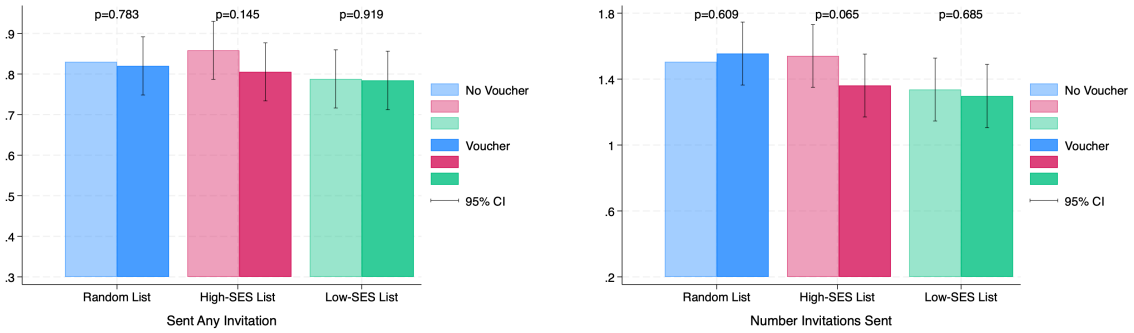


Figure 4: First Stage Invitation Sending

In the Inviter treatment arms where participants saw *only* Low-SES Guest names or *only* High-SES Guest names, there are no differences in the probability of sending an invitation with or without the voucher. The model predicts that the of value of socialization with High- and Low-SES women changes across the domain *relative to one another*. However, the way in which the marginal utility of homophilic and non-homophilic relationships changes across the effort domain *relative to the marginal utility of household consumption* is ambiguous. The evidence is consistent with a model where the relationship between the marginal utility of sending an invitation relative to the marginal utility of personal consumption remaining constant across the effort domain, regardless of the degree of homophily in the relationship.

Inviters with the Random Guest List also do not change the total number of invitations that they send with the voucher, consistent with a model where the marginal utility of a social relationship relative to the the marginal utility of personal consumption is constant across the effort domain. However, when Inviters with the Random Guest List have the voucher, they are more likely to invite High-SES Guests (Table 1), consistent with Model Prediction 3.

In the Inviter group with the High-SES Guest List, the number of invitations decreased slightly with the voucher. However, we see equivalent rates of *actual* shared meals, and higher rates of sharing meat (Figure 5). This could indicate that the marginal utility of effort into relationships with high-SES women is actually *increasing* in effort. When a high-effort activity is subsidized, Inviters invest more effort into *each individual* High-SES Guest, rather than diffusing lower levels of effort across multiple women.

5.2 Heterogeneity

The model predicts that people with a high marginal *instrumental* utility of social relationships should have the largest increases in effort towards non-homophilic links, relative to their effort

Table 1: Any invitation sent to...

	(1) Any	(2) Any	(3) Any	(4) Low-SES	(5) Low-SES	(6) High-SES	(7) High-SES
Random + Voucher	-0.009	-0.005	-0.003	0.011	0.017	0.085**	0.089**
	(0.037)	(0.036)	(0.037)	(0.042)	(0.040)	(0.040)	(0.038)
High-SES	0.028	0.057	0.066*			0.319***	0.071
	(0.036)	(0.037)	(0.039)			(0.039)	(0.050)
High-SES + Voucher	-0.025	-0.000	0.003			0.263***	0.011
	(0.036)	(0.036)	(0.038)			(0.039)	(0.051)
Low-SES	-0.042	-0.008	-0.011	0.268***	0.013		
	(0.037)	(0.037)	(0.040)	(0.042)	(0.054)		
Low-SES + Voucher	-0.044	-0.012	-0.001	0.265***	0.006		
	(0.037)	(0.037)	(0.040)	(0.042)	(0.055)		
Observations	1200	1200	994	800	800	800	800
Control Mean	1.505	1.505	1.468	0.750	0.750	0.755	0.755
Controls for Number of Type on List	NO	YES	NA	NO	YES	NO	YES
P-values:							
High-SES: Voucher = No Voucher	0.146	0.116	0.111			0.154	0.117
Low-SES: Voucher = No Voucher	0.948	0.917	0.805	0.949	0.861		
Random + Voucher = High-SES + Voucher	0.667	0.901	0.860			0.000	0.127
Random + Voucher = Low-SES + Voucher	0.342	0.836	0.950	0.000	0.840		

Standard errors in parentheses
All specifications include baseline unbalanced control variables (moved to the village for marriage), geographic cluster fixed effects, cluster-specific wealth quintile fixed effects, and lasso-selected controls. Column 3 drops Inviter participants who saw fewer than six names on the Sharing List (206 participants, or 17 percent).
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

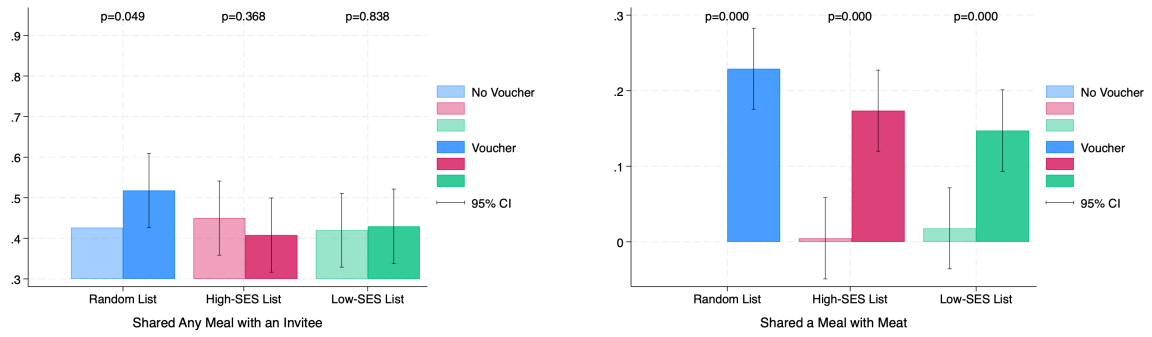


Figure 5: First-Stage Meal Sharing

into homophilic links, as effort increases. In other words, they should be the most sensitive to the voucher in shifting away from Low-SES Guests and towards High-SES Guests. Because these model predictions concern the *relative* preferences for more and less-homophilic links at different margins of effort, the following analysis is conducted only in the Inviter group with the Random Guest List, which is the only group trading off between socialization effort into high-SES and low-SES links.

	(1) Number of Invitations to Any SES Invitees		(2) Number of Invitations to High-SES Invitees		(3) Number of Invitations to Low-SES Invitees	
Less Credit Available	0.241	(0.165)	0.011	(0.126)	0.230*	(0.120)
Voucher	0.081	(0.118)	0.009	(0.090)	0.072	(0.086)
Less Credit × Voucher	-0.103	(0.217)	0.299*	(0.165)	-0.402**	(0.157)
Observations	400		400		400	
No Voucher Mean	1.485		0.769		0.716	

Standard errors in parentheses
All specifications control for baseline unbalanced variables (moved to the village for marriage), geographic cluster fixed effects, cluster-specific wealth quintile fixed effects, and lasso-selected baseline variables.
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Number of Invitations Sent to Guests by Guest SES (Random Guest List)

As a proxy for having a high marginal instrumental utility of social relationships, I create a variable indicating people with few borrowing opportunities at baseline: people with no more than one person who they borrowed from in the past year who are also not a part of VSLA (32% of the sample).[13] Consistent with Model Prediction 1, I find that Inviters with few borrowing opportunities decrease the number of invitations to low-SES women when they have the voucher, and increase the number of invitations to high-SES women (Table 3).

	(1) Number of Invitations to Any SES Invitees		(2) Number of Invitations to High-SES Invitees		(3) Number of Invitations to Low-SES Invitees	
Loneliness or Depression Risk	-0.147	(0.151)	-0.058	(0.116)	-0.089	(0.111)
Voucher	-0.040	(0.123)	0.111	(0.095)	-0.151*	(0.090)
At Risk × Voucher	0.257	(0.202)	-0.021	(0.155)	0.278*	(0.148)
Observations	400		400		400	
No Voucher Mean	1.543		0.784		0.759	

Standard errors in parentheses
All specifications control for baseline unbalanced variables (moved to the village for marriage), geographic cluster fixed effects, cluster-specific wealth quintile fixed effects, and lasso-selected baseline variables.
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Number of Invitations Sent to Guests by Guest SES (Random Guest List)

The model predicts that people with high marginal *direct* utility of socialization will have the smallest increase in effort towards non-homophilic links, relative to their effort into homophilic

[13] I pre-registered a heterogeneity analysis by having few borrowing social network links at baseline. I did not pre-register heterogeneity analysis by baseline VSLA participation. However 42% of people with few borrowing social network links are VSLA members. These people may even have the *easiest* time accessing credit, if the adequacy of their VSLA membership is precisely why they do not demand informal credit. Consequently, the pre-registered measure of people with few borrowing network links, including VSLA members, is in practice not a good measure for people with high marginal instrumental utility.

links, as effort increases. Among this group, there may even be a reverse pattern, whereby individuals increase their effort towards *homophilic* links, relative to non-homophilic links, as effort increases. I use women with a high baseline risk of loneliness a proxy for having a high marginal direct utility of social relationships. Thirteen percent of the sample is classified as lonely. For Inviters who are lonely, the voucher does not change the number of invitations they send to High-SES Guests. Conversely, the voucher leads lonely women to *increase* the number of invitations they send to to Low-SES Guests. This is especially remarkable considering that 47% of lonely women also have few borrowing opportunities.

5.3 Meal-Sharing Across Treatment Sub-Groups

While 81% of Inviters sent at least one invitation to a Guest, only 45% of Inviters ultimately shared a meal with an Invitee. While the effort cost of invitation-sending was significantly reduced by the intervention, the effort cost of meal-sharing was not. Enumerators often sent the invitations unaccompanied by the Inviter, meaning that the Guest would have to take the initiative to go to the Inviter's house (to plan a time to share a meal or see if she could join for a meal in that moment), or the Inviter would have to find the Guest at another time and follow up on the enumerator-delivered invitation. The sharp drop-off in take-up at this stage where participants needed to bear the effort cost of socialization provides further evidence that these costs are steep and often prohibitive.

Meal-sharing with a Guest was non-differentiable across the Inviter groups with High-SES Guests and Low-SES Guests (Table 4). I cannot rule out that $c^{SH}_{\theta_{LSES}\theta_{HSES}} = c^{SH}_{\theta_{LSES}\theta_{LSES}}$, or that there are no differences in the effort cost that a low-SES woman bears in sharing a meal with a low-SES woman versus a high-SES woman. Furthermore, I cannot rule out that $P_{\theta_{LSES}\theta_{HSES}} = P_{\theta_{LSES}\theta_{LSES}}$, or that the probability of mutual consent is non-differential for homophilic versus non-homophilic matches. Interestingly, however, the rate of meal-sharing is higher for Inviters with the Random Guest List *with the voucher*.

This is largely driven by increases in meals with high-SES Guests, but I cannot rule out that there is also an increasein meals with low-SES Guests. This suggests that selection allows participants to optimize on match quality.

5.4 Meeting and Friending Bias Accounting

The social networks literature identifies two biases that lead to homophily: friending bias, or a higher probability of becoming friends with a same-type person *conditional* on meeting them; and meeting bias, or a higher probability of meeting a same-type person in the first place. These biases are often viewed as the roles of preferences (friending bias) and constraints (meeting bias). Descriptively, both meeting bias and friending bias contribute to homophily (Currarini et al., 2010; Chetty et al., 2022b).

However, meeting opportunities are *not* exogenously given. In the case of biased opportunities,

Table 4: Shared any meal with...

	(1) Any	(2) Any	(3) Low-SES	(4) Low-SES	(5) High-SES	(6) High-SES
Random + Voucher	0.093**	0.096**	0.042	0.046	0.100**	0.102**
	(0.046)	(0.046)	(0.043)	(0.043)	(0.044)	(0.043)
High-SES	0.014	0.031			0.189***	0.050
	(0.047)	(0.047)			(0.044)	(0.057)
High-SES + Voucher	-0.021	-0.006			0.167***	0.026
	(0.047)	(0.047)			(0.044)	(0.057)
Low-SES	0.000	0.020	0.173***	0.043		
	(0.046)	(0.047)	(0.043)	(0.057)		
Low-SES + Voucher	0.008	0.027	0.205***	0.074		
	(0.047)	(0.047)	(0.044)	(0.058)		
Observations	1190	1190	796	796	791	791
Control Mean	0.401	0.401	0.215	0.215	0.220	0.220
Controls for Number of Type on List	NO	YES	NO	YES	NO	YES
P-values:						
High-SES: Voucher = No Voucher	0.443	0.415			0.615	0.572
Low-SES: Voucher = No Voucher	0.859	0.871	0.450	0.479		
Random + Voucher = High-SES + Voucher	0.013	0.028			0.119	0.187
Random + Voucher = Low-SES + Voucher	0.068	0.145	0.000	0.630		

Standard errors in parentheses
All specifications include baseline unbalanced control variables (moved to the village for marriage), geographic cluster fixed effects, cluster-specific wealth quintile fixed effects, and lasso-selected controls.
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

homophily arises because people don't have as many opportunities to meet different-type individuals – but selection into meeting opportunities could be correlated with, or even *driven* by, preferences for homophily. In the case of biased preferences, homophily arises because people simply prefer interacting with same-type individuals. However, if meetings are not exogenous, friending bias is measured on a selected group. Furthermore, it is feasible that constraints could be an important contributor to friending bias.[14] While rich descriptive data can quantify meeting and friending bias, it cannot determine the degree to which preferences and constraints *drive* each bias. Consequently, it is problematic to conflate meeting bias with constraints and friending bias with preferences, and descriptive data cannot adequately inform us if supply-side or demand-side forces drive homophily.

First, I exogenously measure the role of preferences as a driver of meeting bias, both under high- and low-price regimes. Next, I measure friending bias conditional on exogenous meeting opportunities.

Meeting Bias

I am not able to measure meeting bias directly, because I do not record real-world meeting opportunities. However, I can measure the extent to which preferences and high prices drive meeting bias. To do this I consider: to what extent do Inviters substitute *away* from sending

[14]If, for example, individuals are missing the resources or skills to link with a different-type person, even after meeting them. For example, people from cultural backgrounds may have different ways of communicating to one another that they are interested in forming a relationship.

invitations to high-SES Guests when they have the opportunity to choose, as compared to the extent that Inviters substitute away from inviting low-SES Guests when they have the opportunity to choose. Comparing these two estimates in the group *without* the voucher gives me a measure of the role of preferences in driving meeting bias under a high-price regime. Comparing these two estimates in the group *with* the voucher gives me a measure of the role of preferences in driving meeting bias under a low-price regime.

My empirical specification is the following:

$$InviteLSES_i = \beta_0^L + \beta_1^L L_i + \gamma_i + \theta_i + X_i + \epsilon_i$$

$$InviteHSES_i = \beta_0^H + \beta_1^H H_i + \gamma_i + \theta_i + X_i + \epsilon_i$$

where the first regression is estimated among Inviters with Low-SES or Random Guest Lists, and the second regression is estimated among Inviters with High-SES or Random Guest Lists. $InviteLSES_i$ is the number of invitations an Inviter sent to a Low-SES Guest, and $InviteHSES_i$ is the number of invitations an Inviter sent to a High-SES Guest. L_i and H_i indicate, respectively, if a participant was an Inviter with a Low-SES Guest List or a High-SES Guest List (in both regressions, Inviters with the Random Guest List are the omitted group). Let γ_i be geographic-cluster fixed effects, θ_i be wealth-quintile fixed effects, and X_i be a matrix of unbalanced baseline variables and lasso-selected controls.

Let $\beta_1^{L,NV}$ and $\beta_1^{H,NV}$ represent β_1^L and β_1^H estimated on the samples *without* the voucher, and let $\beta_1^{L,V}$ and $\beta_1^{H,V}$ represent β_1^L and β_1^H estimated on the samples *with* the voucher. Then $\beta_1^{H,NV} - \beta_1^{L,NV}$ measures preferences-in-meeting bias under a high-price regime (the additional number of invitations someone sends to a homophilic link relative to a non-homophilic link, when they have the ability to exercise preferences versus not); $\beta_1^{H,V} - \beta_1^{L,V}$ measure preferences-in-meeting bias under a low-price regime; and $(\beta_1^{H,NV} - \beta_1^{L,NV}) - (\beta_1^{H,V} - \beta_1^{L,V})$ measures the number of invitations to homophilic links induced *because* of high prices.

I find that preferences for homophily are an important driver of meeting bias, but that this pattern is only true in the high-price regime. Among Inviters without the voucher, Inviters with the Random Guest List send 0.790 fewer invitations to High-SES Guests than Inviters with the High-SES Guest List (Table 5). Inviters with the Random Guest list only send 0.606 fewer invitations to Low-SES Guests than Inviters with the Low-SES Guest List. The difference between these two estimates is 0.184 invitations, and is just shy of conventional levels of statistical significance ($p = 0.118$). In other words, when Inviters do not have the ability to exercise preferences over the SES of the women who they invite, they have the same propensity to invite low-SES and high-SES women. However, when they can choose, they are more likely to invite Low-SES women.

This pattern *does not* hold when we evaluate the sample of Inviters who had the voucher. Inviters with the Random Guest List send 0.527 fewer invitations to High-SES Guests than Inviters with the High-SES Guest List, while Inviters with the Random Guest list only send 0.609

fewer invitations to Low-SES Guests than Inviters with the Low-SES Guest List. The difference between these two estimates is -0.082, indicating that the biased preference for homophily is completely eliminated by the voucher. Comparing the preferences-in-meeting bias across the high-price and low-price regimes, I find that high prices lead to an additional 0.266 invitations per person to low-SES women, just shy of conventional levels of statistical significance ($p = 0.110$).

Friending Bias

These results imply that there is a high degree of selection into meeting opportunities under "real-world" conditions (Inviters with the Random Guest List, without the voucher) that is endogenous to demand for homophily. This implies that standard measures of friending bias may be mismeasured.

To test for friending bias, I will consider an Inviter and a Guest as "linked" if the Inviter reports that, one month after the intervention, she has the phone number of the Guest saved. In order to compare rates of friending among Inviters with what we would expect without the intervention, I asked Control participants if they had the phone numbers of a random placebo list of women, selected by the same methodology that Guest Lists were designed.

My empirical specification is the following:

$$PhoneLSES_i = \beta_0^L + \beta_1^L L_i + \gamma_i + \theta_i + X_i + \epsilon_i$$

$$PhoneHSES_i = \beta_0^H + \beta_1^H H_i + \gamma_i + \theta_i + X_i + \epsilon_i$$

where $PhoneLSES_i$ is the number of low-SES Guest phone numbers that the Inviter has saved, and $PhoneHSES_i$ is the number of high-SES Guest phone numbers that the Inviter has saved.

Consistent with preferences for homophily driving *meeting bias*, I find no evidence of friending bias conditional on *exogenous* meeting opportunities: there is no difference in the propensity for Inviters to have the phone number of the women on the Guest List saved across the Inviters with a Low-SES Guest List and Inviters with a High-SES Guest List, with or without the voucher. However, consistent with descriptive data (where we would never see these exogenous meeting opportunities take place), I find positive and significant friending bias conditional on *endogenous* meeting opportunities: without the voucher, Inviters with the Random Guest List are 4.1 percentage points (241%, $p = 0.032$) more likely to have the phone number of a Low-SES Guest saved at endline than a High-SES Guest. Interestingly, for Inviters with the Random Guest List *and* the voucher, patterns of friending looks more similar to patterns among women with exogenous meeting opportunities: there are no differences in saving the phone numbers of high- or low-SES women. Although I cannot statistically rule out equality between friending bias with or without the voucher, this pattern implies that constraints such as high prices may still play a role in friending bias.

In conclusion, this exercise shows that high prices of high-value social goods act as an important

	(1)	(2)	(3)	(4)
	Low-SES vs. Random	High-SES vs. Random	Low-SES + Voucher vs. Random + Voucher	High-SES + Voucher vs. Random + Voucher
Outcome: Number of Invitations to Low-SES Invitees	0.606***		0.609***	
	(0.094)		(0.094)	
Outcome: Number of Invitations to High-SES Invitees		0.790***		0.527***
		(0.090)		(0.095)
Observations	397	394	399	397
Control Mean	0.750	0.755	0.700	0.885
DD: (H–R) – (L–R)	0.184 [p= 0.118]		-0.082 [p= 0.486]	
DDD: [(H–R) – (L–R)] – [(H+V – R+V) – (L+V – R+V)]	0.266 [p= 0.110]			

Standard errors in parentheses

* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Meeting Bias

	(1) Low-SES Numbers Saved		(2) High-SES Numbers Saved	
High-SES × No Voucher			0.057***	(0.018)
High-SES × Voucher			0.022	(0.018)
Low-SES × No Voucher	0.029*	(0.016)		
Low-SES × Voucher	0.036**	(0.017)		
Random × No Voucher	0.025	(0.016)	-0.015	(0.018)
Random × Voucher	0.018	(0.016)	0.003	(0.018)
Observations	1134		1143	
Control Mean	0.016		0.032	
Random DD: L – H	0.041 [p= 0.032]			
Random DD: L+V – H+V	0.015 [p= 0.482]			
Random DDD: [L – H] – [L+V – H+V]	0.026 [p= 0.257]			
LSES/HSES DD: L – H	-0.028 [p= 0.284]			
LSES/HSES DD: L+V – H+V	0.014 [p= 0.571]			
LSES/HSES DDD: [L – H] – [L+V – H+V]	-0.041 [p= 0.192]			

Standard errors in parentheses

* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Friending Bias

driver of homophily, and that using measures of meeting bias and friending bias from descriptive data cannot give a full accounting for how preferences shape homophily. Preferences for homophily drive *meeting bias*, which then directly drives friending bias because meeting opportunities are selected. In the absence of meeting bias, friending bias does not arise. This is consistent with the "inter-group contact theory", whereby people have a preference for homophily (or, in the case of the original theory a la Allport (1954), have prejudice towards out-group members) precisely because they have not interacted in a setting that can create meaningful connections, such as a shared meal.

6 Results: Downstream Effects

6.0.1 Instrumental Utility

I find that exogenous opportunities to meet high-SES women leads to a large increase in earning income through sales, which I refer to as "business" (Table 7). Note that many of these businesses involve informal transactions, such as selling baked goods on the road-side or vegetables to other villagrs, and do not require formal business activity nor a brick-and-mortar business space. These effects are largely driven by new businesses, many of which are directly copied from the business of a high-SES Guest.[15] There are no effects on business among Inviters with the Low-SES Guest List. Among Inviters with the Random Guest List, there were positive but smaller impacts on businesses. I view these impacts as an impact on diversified and improved income streams, rather than occupational sorting, because there is little substitution out of other income-earning activities – namely, subsistence agricultural cultivation and piecework casual labor (Table E.1).

	(1) Business		(2) New Business		(3) Business Copying		(4) Business Capital	
High-SES × No Voucher	0.098***	(0.032)	0.076**	(0.030)	0.039**	(0.020)	0.098	(0.075)
High-SES × Voucher	0.090***	(0.032)	0.060**	(0.029)	0.039**	(0.020)	0.136*	(0.074)
Low-SES × No Voucher	0.011	(0.032)	-0.006	(0.029)	-0.016	(0.020)	0.006	(0.074)
Low-SES × Voucher	0.023	(0.032)	-0.003	(0.030)	-0.005	(0.020)	0.002	(0.075)
Random × No Voucher	0.052*	(0.032)	0.042	(0.030)	0.038*	(0.020)	0.026	(0.074)
Random × Voucher	0.030	(0.032)	0.036	(0.029)	-0.003	(0.020)	-0.034	(0.074)
Observations	1586		1586		1586		1587	
Control Mean	0.179		0.129		0.048		-0.011	

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Downstream Business Outcomes

However, these businesses *do not* translate into increased liquidity for Inviters with the opportunity to invite a high-SES guest (Table 8). There is suggestive evidence that, for Inviters with the opportunity to invite high-SES guests, the voucher leads to an increase in liquidity. Among Inviters with the opportunity to invite a high-SES guest, the voucher leads to a 0.097 SD increase on an index of earning, consumption, and savings, though this difference is not statistically significant ($p = 0.206$). In this group, the voucher leads to a statistically significant 9.3 percentage point increase in the probability of taking out a loan in the previous month ($p = 0.065$). The voucher *only* leads to an increase in borrowing among Inviters with the High-SES Guest List if participants were credit-constrained at baseline (Table 9). This is consistent with the model prediction that people who receive the *least* baseline financial return from their social network will be the *most* sensitive to price in their ability to realize a financial return from new high-SES links.

The Inviter treatment actually leads to negative effects on liquidity when participants have the opportunity to only invite a low-SES guest. This suggests that meal-sharing indeed is a

[15] Business copying is defined as being in the Guest's *baseline* business, for people who were *not* in that business at baseline.

financially costly action. The voucher leads to no changes among Inviters with the Low-SES Guest List. Inviters with the Random Guest List experience a large positive impact of the treatment on liquidty, without increases in borrowing. This suggests that they could be better-matched in their occupations. Their businesses are more profitable, and people who can earn significant amounts of income doing piece-work *do not* transition into sales.

	(1) Liquidity Index		(2) Borrowed	
High-SES × No Voucher	-0.032	(0.066)	-0.062	(0.044)
High-SES × Voucher	0.065	(0.066)	0.031	(0.043)
Low-SES × No Voucher	-0.111*	(0.066)	-0.047	(0.043)
Low-SES × Voucher	-0.064	(0.066)	-0.049	(0.043)
Random × No Voucher	0.151**	(0.066)	-0.073*	(0.043)
Random × Voucher	0.049	(0.066)	-0.013	(0.043)
Observations	1586		1366	
Control Mean	-0.000		0.488	
P-values:				
High-SES: V=NV	0.206		0.065	
Low-SES: V=NV	0.534		0.966	
Random: V=NV	0.178		0.233	

Standard errors in parentheses
The liquidity index is a PCA index of the following variables that represent consumption, savings, and earnings: kilograms of maize (kernels and flour) in storage (winsorized), the number of times the participant ate animal proteins in the past month, if the participant typically consumes white maize flour (the most expensive type of maize flour), the average number of meals she eats per day, the amount she earned from work in the past month (winsorized), and the amount others in the household earned from work in the past month (winsorized).
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Downstream Liquidity Outcomes

	(1) Borrowed Last Month More Credit-Constrained		(2) Borrowed Last Month Less Credit-Constrained	
High-SES × No Voucher	-0.185**	(0.074)	-0.014	(0.055)
High-SES × Voucher	0.014	(0.071)	0.027	(0.054)
Low-SES × No Voucher	-0.117	(0.079)	-0.033	(0.051)
Low-SES × Voucher	-0.086	(0.072)	-0.038	(0.055)
Random × No Voucher	-0.116	(0.074)	-0.069	(0.054)
Random × Voucher	-0.068	(0.071)	0.010	(0.055)
Observations	474		892	
Control Mean	0.421		0.528	
P-values:				
High-SES: V=NV	0.019		0.515	
Low-SES: V=NV	0.723		0.932	
Random: V=NV	0.561		0.207	

Standard errors in parentheses
The outcome is an indicator for if the participant borrowed (formally or informally) in the past month. Women are considered if, at baseline, they were not a member of VSLA and borrowed from no more than one person in the past year. Women are considered if, at baseline, they were a member of VSLA or borrowed from two or more people in the past year.
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Downstream Borrowing Heterogeneity

6.0.2 Direct Utility

The Inviter treatment with the Low-SES Guest List leads to a meaningful increase in perceived acceptance from others in the village among women who were lonely or depressed at baseline (Table 10). This is true with or without the voucher. On average, across all Inviters with the Low-SES Guest List, there are larger treatment effects on perceived acceptance with the voucher than without, though the difference is not statistically significant.

In the Inviter group with the Random Guest List, there are large positive treatment effects on perceived acceptance among the group *without* the voucher regardless of baseline mental health.

	(1) Perceived Acceptance Either Lonely or Depressed		(2) Perceived Acceptance Neither Lonely nor Depressed	
High-SES × No Voucher	0.028	(0.140)	0.090	(0.083)
High-SES × Voucher	0.095	(0.133)	0.104	(0.085)
Low-SES × No Voucher	0.250*	(0.145)	0.019	(0.082)
Low-SES × Voucher	0.258*	(0.138)	0.079	(0.084)
Random × No Voucher	0.209	(0.130)	0.159*	(0.087)
Random × Voucher	-0.050	(0.131)	-0.041	(0.085)
Observations	566		1020	
Control Mean	-0.169		0.016	
P-values:				
High-SES: V=NV	0.672		0.883	
Low-SES: V=NV	0.962		0.520	
Random: V=NV	0.075		0.047	

Standard errors in parentheses
The outcomes is a PCA index of two variables: agreement with the statement (Likert scale), and agreement with the statement (Likert scale, reverse-coded). Women are coded as lonely at baseline if they scored a 6 or greater on the UCLA-3 loneliness scale. Women are coded depressed at baseline if they scored a 10 or greater on the CESDR-10 scale.
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Downstream Perceived Acceptance Heterogeneity

7 Conclusion

My results add to our understanding of social network formation in three important ways. First, I find that information frictions and effort costs of the activities that form or strengthen network links are prohibitive, but that they are remarkably easy to overcome. This is true for *both* cross-SES and within-SES links. If the Sharing List, which is little more than a nudge, leads to such high take-up of invitation-sending, and meal-sharing has such large benefits even without the voucher, why don't people share more meals with each other in the absence of the intervention? Baseline vignettes and survey questionnaires indicate that there may be misperceptions in the community about *other's* willingness to engage in meal-sharing (this pluralistic ignorance is discussed in more depth in Section 2.3).

I find evidence that people with the most pessimistic beliefs are the people most likely to change their meal-sharing behavior at endline. At baseline, I asked participants: "Thinking about ten

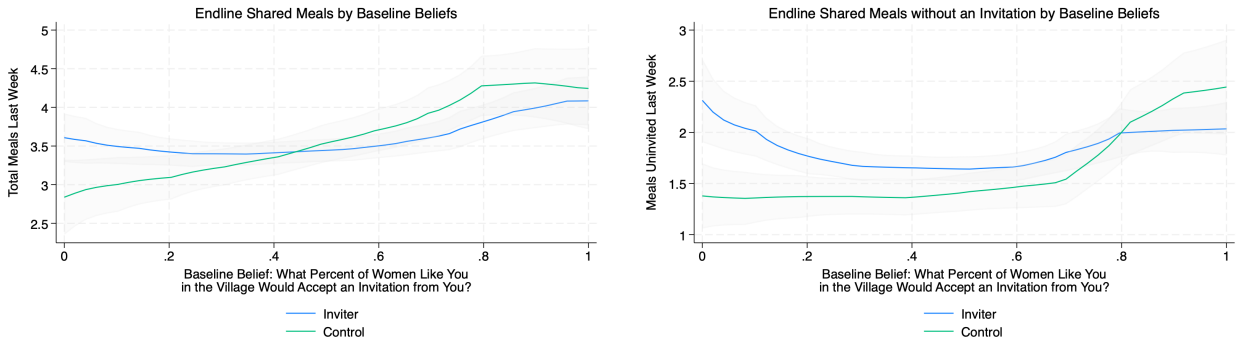


Figure 6: Baseline Beliefs and Endline Meal-Sharing

other women who are similar to you in the village, how many do you think would accept an invitation for a shared meal with you?" At endline, I asked participants how many meals they shared with other people outside the household in the past week. I find that Inviters with the *most* pessimistic views at baseline share more meals in the past week than Control participants with pessimistic views (Figure 6). In fact, among participants who thought that around 45% of women in the village would accept her invitation – or, the women whose beliefs should *not* update from being in the Inviter treatment, since 45% of Inviters ended up sharing meals with Guests – there is no gap between Inviter and Control group meal-sharing in the past week. Notably, the nature of meal-sharing changes, even among more optimistic Inviters. Meals are more often shared without an invitation after experiencing the Inviter treatment (both hosted and visited meals).

Secondly, I show that the high prices of high-value "social lubricants" prevent valuable cross-SES interactions and contribute to the persistence of income-based homophily. This has important implications for community-based interventions. Without considering the *prices* of social interaction, links may form or strengthen in specific ways that may even reinforce existing inequities. A simple implication of this experiment for policy is that, when introducing self-help financial groups for which women form groups themselves, such as VSLA, providing lower-income women with vouchers for "social lubricant" goods can help them to be included.

Third, I show that treatment effects are largest, and most varied across a wide array of outcomes, among Inviters who can choose the SES of the Guests who they invite for a meal. This has implications for our interpretation of descriptive data documenting large benefits of cross-SES interactions. The links that we observe in descriptive data are only the self-selected links, and thereby the set of links that are most likely to benefit from cross-SES relationships. Thus, we should not expect similar benefits on average if a representative group is given exogenous opportunities for cross-SES linking. However, importantly, this also implies that people may have accurate knowledge about the types of relationships from which they can most benefit, and that providing choice in social interventions may be the best way to maximize the benefits of social interactions.

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Online Supplementary Material

Appendix A Background and Cultural Context

A.1 Additional Figures and Tables

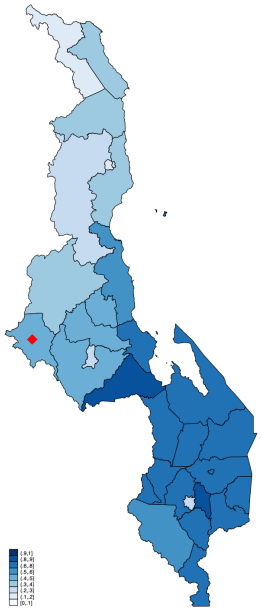


Figure A.1: Percent of Women Who Never Left Their Home Village (Malawi DHS, 2015)

	(1) Ever Moved Villages	(2) Ever Moved Villages	(3) Ever Moved Villages	(4) Ever Moved Villages
Property Owner	-0.287***	-0.222***	-0.277***	-0.220***
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	67987	67987	67987	67987
Mean of Women				
Without Owned Property	0.677	0.677	0.677	0.677
District Fixed Effects		X		X
Tribe Fixed Effects			X	X

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table A.1: Malawi DHS 2015: Determinants of Moving Villages

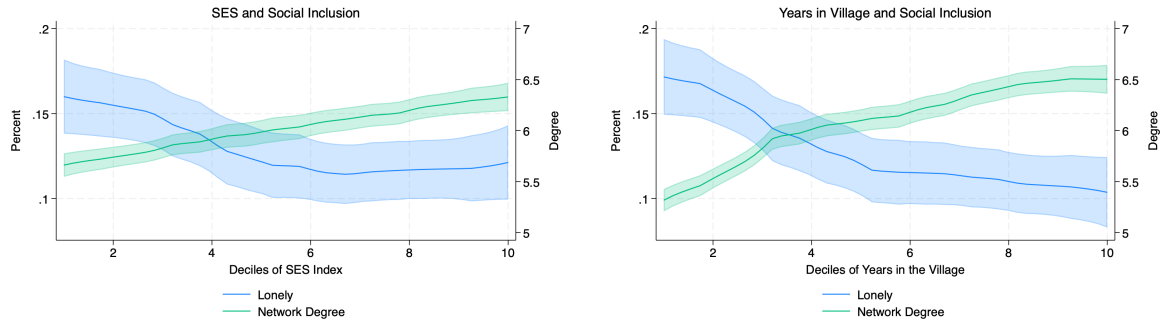


Figure A.2: Social Inclusion – by SES and Years in the Village

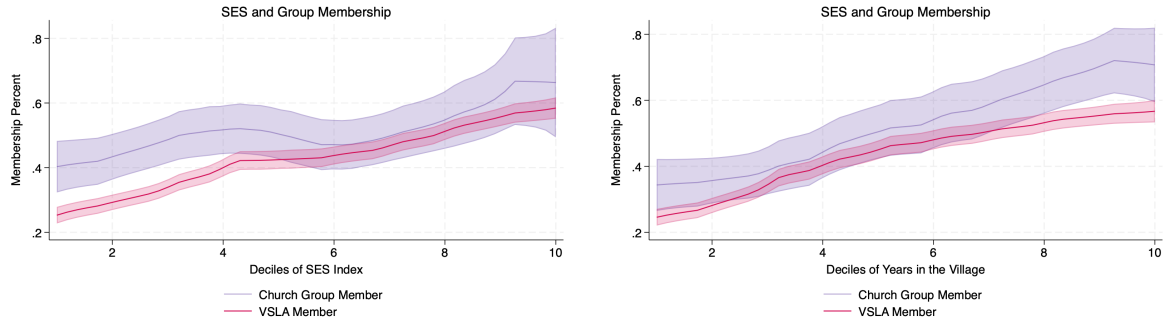


Figure A.3: Group Membership – by SES and Years in the Village

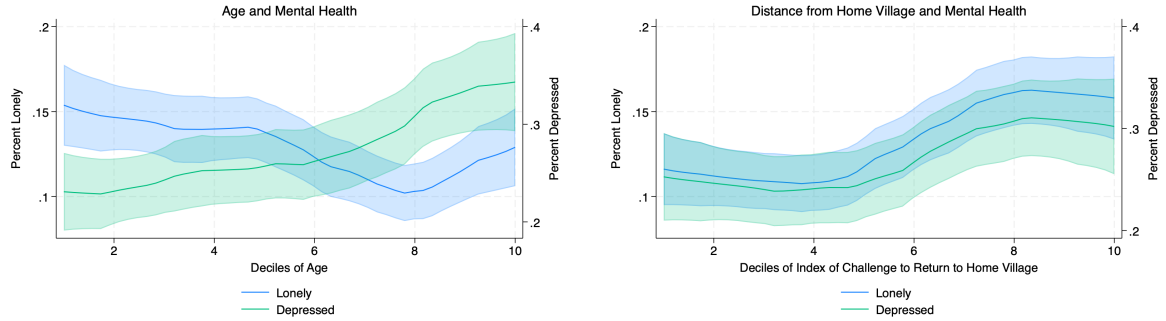


Figure A.4: Mental Health – by Age and Distance from Home Village

	Low-SES	**Thatched**	**High-SES**	**Iron Sheets**
Iron Sheets Roof	0.26		0.84	
Any HH Business	.39	.43	.76	.53
Acres of Owned Farmland	1.7	1.8	3.0	2.3
Meals in Past 2 Days	4.5	4.5	4.9	4.7
Months Consuming Harvest	4.5	4.3	5.5	5.2
Acres of Rented Farmland	0.8	0.7	1.1	1.2
Any HH Sec.-School Grad.	0.13	0.10	0.20	0.22

Table A.2: Summary Statistics by Socio-Economic Status

	(1) Full Sample	(2) Thinking About a Meal-Sharing Friend	(3) Thinking About a Work Friend	(4) Female Sample	(5) Male Sample
Conversation Over a Meal	1.282***	1.276***	1.303***	1.249***	1.452**
	(0.150)	(0.212)	(0.161)	(0.159)	(0.443)
Friend from Work	0.020			0.023	-0.000
	(0.119)			(0.134)	(0.256)
Observations	504	252	252	432	72
Mean in Other Settings	2.045	2.042	2.048	2.123	1.574

Standard errors in parentheses

The outcome is how personal a conversation could become in a given setting, and with a given person, on a scale from 1 to 5 (where higher numbers indicate more personal conversations). Each survey participant was asked to consider a conversation across four settings: over a meal, while working, while doing chores, or while at work. They were also asked to consider two types of people: a person with whom they often share meals, and a person with whom they often work together. The order of questions was randomized. Each observation is at the question level (with eight observations per participatn). All regressions include individual fixed effects and fixed effects for the order in which they were asked the question. Standard errors are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A.3: Closeness of a Conversation Across Settings

Figure A.5: Religion-Based Village-Level Homophily

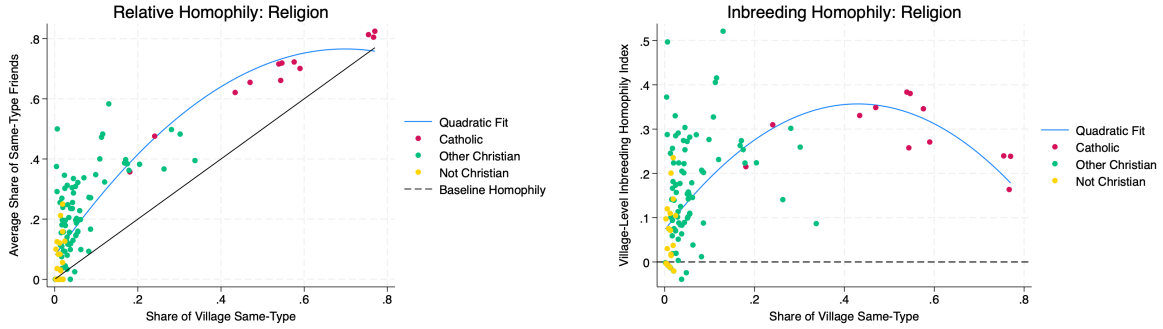


Figure A.6: Asset-Based Village-Level Homophily

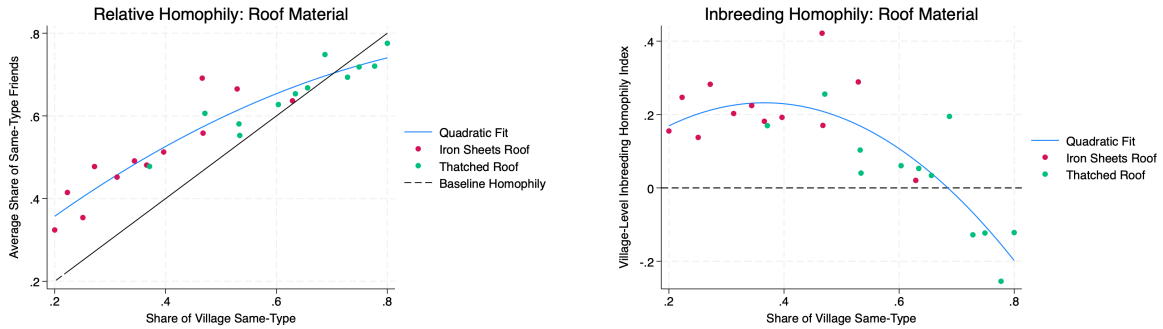


Figure A.7: Education-Based Village-Level Homophily

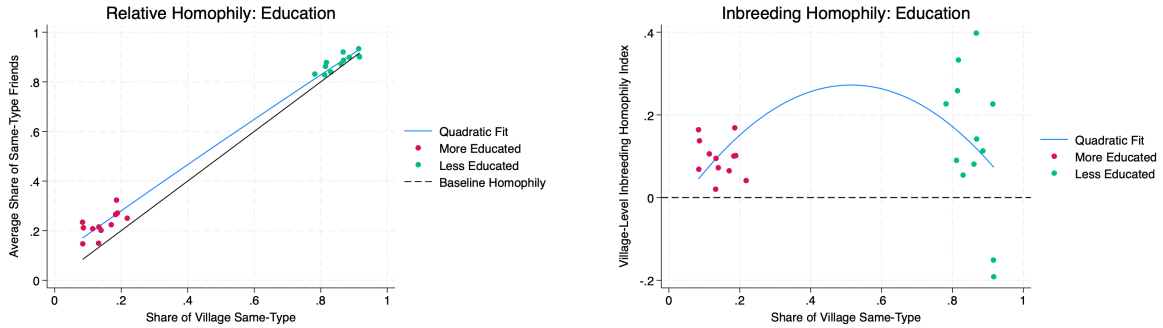
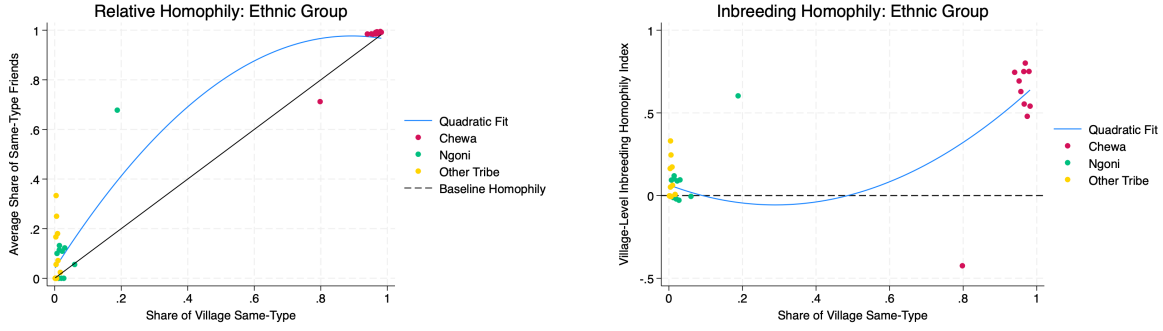


Figure A.8: Ethnicity-Based Village-Level Homophily



Appendix B Baseline Balance Tables

Variable	(1) Inviter: Random SES Mean/SE	(2) Inviter: High-SES Mean/SE	(3) Inviter Low-SES Mean/SE	T-test Difference (1)-(2)	T-test Difference (1)-(3)
Age	0.005	-0.098	-0.033	0.103	0.038
	(0.062)	(0.054)	(0.058)		
Years in Village	-0.061	-0.088	-0.149	0.027	0.088
	(0.041)	(0.048)	(0.052)		
Chewa	-0.062	0.010	-0.026	-0.073	-0.036
	(0.088)	(0.066)	(0.071)		
Number of Children	0.007	-0.070	-0.110	0.077	0.117
	(0.046)	(0.057)	(0.051)		
SES Index (Z-Score)	-0.340	-0.362	-0.374	0.022	0.035
	(0.034)	(0.032)	(0.035)		
Consuming Own Maize	-0.078	-0.046	-0.130	-0.031	0.052
	(0.066)	(0.060)	(0.065)		
VSLA	-0.134	0.003	-0.028	-0.137	-0.106
	(0.054)	(0.063)	(0.061)		
Rented Acres of Farmland	-0.133	-0.011	-0.093	-0.122	-0.040
	(0.050)	(0.059)	(0.047)		
Rented Gardens	0.012	-0.054	0.115	0.066	-0.104
	(0.059)	(0.049)	(0.064)		
Moved for Marriage	0.008	-0.105	-0.169	0.113	0.177*
	(0.065)	(0.070)	(0.074)		
Yearly Home Visits	-0.002	0.091	-0.099	-0.093	0.097
	(0.054)	(0.068)	(0.042)		
Social Network Size	-0.048	-0.032	-0.018	-0.016	-0.029
	(0.049)	(0.061)	(0.054)		
Husband in Social Network Size	0.028	0.076	0.008	-0.047	0.020
	(0.059)	(0.056)	(0.057)		
Listed in Others' Networks	-0.027	-0.011	-0.005	-0.017	-0.022
	(0.063)	(0.055)	(0.058)		
% Network High-SES	-0.038	0.063	-0.061	-0.101	0.023
	(0.066)	(0.086)	(0.086)		
% Network Same Roof Material	0.036	0.106	0.095	-0.070	-0.059
	(0.051)	(0.053)	(0.052)		
UCLA-3 Score	0.106	0.085	0.023	0.021	0.083
	(0.061)	(0.063)	(0.054)		
Average Strength of Network Links	-0.017	-0.018	-0.009	0.001	-0.007
	(0.062)	(0.046)	(0.057)		
N	400	400	400		
Clusters	97	97	95		
F-test of joint significance (F-stat)				0.940	1.576*
F-test, number of observations				800	800

Notes: The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors are clustered at variable cluster_id. Fixed effects using variable strata are included in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B.1: Baseline Balance: Comparing Inviter Sub-groups

Variable	(1) Low-SES Mean/SE	(2) High-SES Mean/SE	(3) High-SES + Voucher Mean/SE	(4) Low-SES + Voucher Mean/SE	T-test Difference (1)-(2)	(1)-(3)	(1)-(4)
Age	0.036	-0.115	-0.080	-0.101	0.151	0.116	0.137
	(0.080)	(0.076)	(0.069)	(0.073)			
Years in Village	-0.065	-0.137	-0.038	-0.233	0.073	-0.027	0.168
	(0.071)	(0.080)	(0.069)	(0.068)			
Chewa	0.010	0.029	-0.008	-0.062	-0.018	0.018	0.073
	(0.078)	(0.073)	(0.081)	(0.086)			
Number of Children	-0.051	-0.045	-0.094	-0.169	-0.006	0.043	0.117
	(0.072)	(0.084)	(0.069)	(0.063)			
SES Index (Z-Score)	-0.328	-0.344	-0.380	-0.421	0.017	0.052	0.094
	(0.040)	(0.038)	(0.043)	(0.045)			
Consuming Own Maize	-0.141	-0.099	0.006	-0.120	-0.042	-0.147	-0.021
	(0.080)	(0.070)	(0.080)	(0.083)			
VSLA	0.084	-0.007	0.013	-0.139	0.091	0.071	0.223
	(0.079)	(0.079)	(0.077)	(0.067)			
Rented Acres of Farmland	-0.101	-0.112	0.090	-0.085	0.012	-0.191	-0.015
	(0.059)	(0.063)	(0.096)	(0.060)			
Rented Gardens	0.012	-0.071	-0.037	0.219	0.083	0.049	-0.207
	(0.088)	(0.071)	(0.067)	(0.077)			
Moved for Marriage	-0.127	-0.098	-0.112	-0.212	-0.028	-0.014	0.085
	(0.088)	(0.085)	(0.087)	(0.091)			
Yearly Home Visits	-0.029	0.068	0.115	-0.169	-0.097	-0.144	0.140
	(0.062)	(0.093)	(0.094)	(0.048)			
Social Network Size	0.010	-0.015	-0.049	-0.046	0.024	0.058	0.056
	(0.070)	(0.077)	(0.071)	(0.084)			
Husband in Social Network Size	0.008	0.103	0.049	0.008	-0.095	-0.041	0.000
	(0.075)	(0.084)	(0.078)	(0.067)			
Listed in Others' Networks	-0.022	0.011	-0.033	0.011	-0.033	0.011	-0.033
	(0.066)	(0.080)	(0.064)	(0.088)			
% Network High-SES	-0.047	0.041	0.085	-0.075	-0.088	-0.131	0.028
	(0.102)	(0.092)	(0.099)	(0.093)			
% Network Same Roof Material	0.046	0.059	0.153	0.144	-0.013	-0.106	-0.098
	(0.077)	(0.060)	(0.076)	(0.069)			
UCLA-3 Score	0.070	0.076	0.094	-0.024	-0.006	-0.024	0.094
	(0.068)	(0.081)	(0.081)	(0.070)			
Average Strength of Network Links	0.030	-0.067	0.032	-0.048	0.097	-0.001	0.079
	(0.072)	(0.055)	(0.068)	(0.080)			
N	200	200	200	200			
Clusters	92	91	94	92			
F-test of joint significance (F-stat)					0.778	1.353	0.772
F-test, number of observations					400	400	400

Notes: The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors are clustered at variable cluster_id. Fixed effects using variable strata are included in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B.2: Baseline Balance: Comparing Voucher Sub-groups

Variable	(1) Random Mean/SE	(2) Random + Voucher Mean/SE	T-test Difference (1)-(2)
Age	0.024	-0.014	0.038
	(0.085)	(0.072)	
Years in Village	-0.098	-0.024	-0.074
	(0.064)	(0.059)	
Chewa	-0.080	-0.044	-0.036
	(0.099)	(0.096)	
Number of Children	0.014	0.001	0.012
	(0.078)	(0.065)	
SES Index (Z-Score)	-0.340	-0.340	-0.000
	(0.041)	(0.043)	
Consuming Own Maize	-0.088	-0.067	-0.021
	(0.084)	(0.072)	
VSLA	-0.119	-0.149	0.030
	(0.072)	(0.076)	
Rented Acres of Farmland	-0.180	-0.087	-0.093
	(0.061)	(0.069)	
Rented Gardens	-0.061	0.084	-0.145
	(0.064)	(0.095)	
Moved for Marriage	0.072	-0.056	0.128
	(0.076)	(0.080)	
Yearly Home Visits	0.001	-0.006	0.007
	(0.055)	(0.081)	
Social Network Size	0.002	-0.097	0.100
	(0.063)	(0.073)	
Husband in Social Network Size	0.062	-0.006	0.068
	(0.074)	(0.074)	
Listed in Others' Networks	-0.022	-0.033	0.011
	(0.077)	(0.069)	
% Network High-SES	-0.096	0.019	-0.115
	(0.076)	(0.080)	
% Network Same Roof Material	0.117	-0.044	0.162
	(0.065)	(0.070)	
UCLA-3 Score	0.134	0.078	0.056
	(0.085)	(0.077)	
Average Strength of Network Links	-0.029	-0.004	-0.025
	(0.088)	(0.076)	
N	200	200	
Clusters	94	93	
F-test of joint significance (F-stat)			0.753
F-test, number of observations			400

Notes: The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors are clustered at variable cluster_id. Fixed effects using variable strata are included in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B.3: Baseline Balance: Comparing Voucher Sub-groups

Variable	(1) Control Mean/SE	(2) Inviter Mean/SE	T-test Difference (1)-(2)
Age	-0.029	-0.042	0.013
	(0.068)	(0.041)	
Years in Village	-0.197	-0.099	-0.097
	(0.044)	(0.029)	
Chewa	0.047	-0.026	0.073
	(0.059)	(0.065)	
Number of Children	-0.108	-0.057	-0.051
	(0.054)	(0.033)	
SES Index (Z-Score)	-0.372	-0.359	-0.014
	(0.039)	(0.027)	
Consuming Own Maize	-0.020	-0.085	0.065
	(0.072)	(0.048)	
VSLA	-0.053	-0.053	0.000
	(0.064)	(0.047)	
Rented Acres of Farmland	-0.093	-0.079	-0.014
	(0.042)	(0.038)	
Rented Gardens	-0.009	0.024	-0.033
	(0.058)	(0.038)	
Moved for Marriage	-0.063	-0.089	0.026
	(0.069)	(0.055)	
Yearly Home Visits	0.016	-0.003	0.019
	(0.050)	(0.035)	
Social Network Size	0.008	-0.033	0.041
	(0.064)	(0.040)	
Husband in Social Network Size	0.055	0.037	0.018
	(0.054)	(0.038)	
Listed in Others' Networks	-0.044	-0.015	-0.029
	(0.055)	(0.045)	
% Network High-SES	-0.050	-0.012	-0.038
	(0.084)	(0.070)	
% Network Same Roof Material	0.082	0.079	0.003
	(0.057)	(0.034)	
UCLA-3 Score	0.031	0.071	-0.040
	(0.042)	(0.041)	
Average Strength of Network Links	-0.069	-0.014	-0.054
	(0.056)	(0.041)	
N	400	1200	
Clusters	94	97	
F-test of joint significance (F-stat)			0.601
F-test, number of observations			1600

Notes: The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors are clustered at variable cluster_id. Fixed effects using variable strata are included in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B.4: Baseline Balance: Comparing Control with Inviters

Appendix C Model Proof

For all $j \neq i$ and all $a \in \mathscr{A}$, we have the following first order conditions:

$$\lambda_V \frac{\partial V_i(a_{ij})}{\partial a_{ij}} + \lambda_Z \frac{\partial Y_i(a_{ij})}{\partial a_{ij}} - \lambda_Z p^a = 0$$

$$\begin{aligned} \text{where} \qquad \lambda_V &= \frac{\partial U_i}{\partial V i(a_{ij})} \\ \lambda_Z &= \frac{\partial U_i}{\partial Z_i} \\ \frac{\partial V_i(a_{ij})}{\partial a_{ij}} &= E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}} \cdot \frac{\partial w_{ij}}{\partial a_{ij}}\Big] \cdot P_{ij} - c^a_{ij} \\ \frac{\partial Y_i(a_{ij})}{\partial a_{ij}} &= E^+\Big[\frac{\partial y_{ij}}{\partial w_{ij}} \cdot \frac{\partial w_{ij}}{\partial a_{ij}}\Big] \cdot P_{ij} \end{aligned}$$

Note that $E^+\Big[\frac{\partial w_{ij}}{\partial a_{ij}}\Big] = w^a$, so $E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}} \cdot \frac{\partial w_{ij}}{\partial a_{ij}}\Big] = w^a \cdot E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}}\Big|_{w_{ij}=w^a}\Big]$. Simplifying and re-arranging, we can derive a condition under individual i will take any specific action a with j:

$$w^a \cdot \left(\lambda_V E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}}\Big|_{w_{ij}=w^a}\Big] + \lambda_Z E^+\Big[\frac{\partial y_{ij}}{\partial w_{ij}}\Big|_{w_{ij}=w^a}\Big]\right) \cdot P_{ij} \geq \lambda_Z p^a + \lambda_V c^a_{ij}$$

We can derive an equilibrium condition for *all* the actions that i will choose to take with j:

$$w_{ij} \cdot \left(\lambda_V E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}}\Big] + \lambda_Z E^+\Big[\frac{\partial y_{ij}}{\partial w_{ij}}\Big]\right) \cdot P_{ij} = \sum_{a \in \mathscr{A}} \lambda_Z p^a + \sum_{a \in \mathscr{A}} \lambda_V c^a_{ij}$$

$$w_{ij} = \frac{\sum_{a \in \mathscr{A}} (\lambda_Z p^a + \lambda_V c^a_{ij})}{\left(\lambda_V E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}}\Big] + \lambda_Z E^+\Big[\frac{\partial y_{ij}}{\partial w_{ij}}\Big]\right) \cdot P_{ij}}$$

Recall that w^a slowly adjusts in responses to changes in p^a in the long-run. Then we can model the change in w_{ij} in response to a temporary price shock by:

$$\frac{\partial w_{ij}}{\partial p^a} = \frac{\lambda_Z}{\left(\lambda_V E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}}\Big] + \lambda_Z E^+\Big[\frac{\partial y_{ij}}{\partial w_{ij}}\Big]\right) \cdot P_{ij}}$$

and this changes along the w_{ij} domain by:

$$\frac{\partial}{\partial w_{ij}}\Big(-\frac{\partial w_{ij}}{\partial p^a}\Big) = \frac{\lambda_Z \cdot \left(\lambda_V E^+\Big[\frac{\partial^2 v_{ij}}{\partial w_{ij}^2}\Big] + \lambda_Z E^+\Big[\frac{\partial^2 y_{ij}}{\partial w_{ij}^2}\Big]\right)}{\left(\lambda_V E^+\Big[\frac{\partial v_{ij}}{\partial w_{ij}}\Big] + \lambda_Z E^+\Big[\frac{\partial y_{ij}}{\partial w_{ij}}\Big]\right)^2 \cdot P_{ij}}$$

PROOF OF PROPOSITION 1:

Consider:

$$\frac{\partial}{\partial w_{\theta_i\theta_{HSES}}}\Big(-\frac{\partial w_{\theta_i\theta_{HSES}}}{\partial p^a}\Big)-\frac{\partial}{\partial w_{\theta_i\theta_{LSES}}}\Big(-\frac{\partial w_{\theta_i\theta_{LSES}}}{\partial p^a}\Big)$$
$$=\frac{\lambda_Z\cdot\Big(\lambda_V E^+\Big[\frac{\partial^2 v_{\theta_i\theta_{HSES}}}{\partial w^2_{\theta_i\theta_{HSES}}}\Big]+\lambda_Z E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w^2_{\theta_i\theta_{HSES}}}\Big]\Big)}{\Big(\lambda_V E^+\Big[\frac{\partial v_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta_{HSES}}}\Big]+\lambda_Z E^+\Big[\frac{\partial y_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta_{HSES}}}\Big]\Big)^2\cdot P_{\theta_i\theta_{HSES}}}$$
$$-\frac{\lambda_Z\cdot\Big(\lambda_V E^+\Big[\frac{\partial^2 v_{\theta_i\theta_{LSES}}}{\partial w^2_{\theta_i\theta_{LSES}}}\Big]+\lambda_Z E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w^2_{\theta_i\theta_{LSES}}}\Big]\Big)}{\Big(\lambda_V E^+\Big[\frac{\partial v_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta_{LSES}}}\Big]+\lambda_Z E^+\Big[\frac{\partial y_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta_{LSES}}}\Big]\Big)^2\cdot P_{\theta_i\theta_{LSES}}}$$

For simplicity, we will use the following expressions:

$$D_1=\Big(\lambda_V E^+\Big[\frac{\partial v_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta_{HSES}}}\Big]+\lambda_Z E^+\Big[\frac{\partial v=y_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta_{HSES}}}\Big]\Big)^2\cdot P_{\theta_i\theta_{HSES}}$$
$$D_2=\Big(\lambda_V E^+\Big[\frac{\partial v_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta_{LSES}}}\Big]+\lambda_Z E^+\Big[\frac{\partial v=y_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta_{LSES}}}\Big]\Big)^2\cdot P_{\theta_i\theta_{LSES}}$$
$$v''=\frac{\partial^2 v_{ij}}{\partial w_{ij}^2}$$

Assume for analysis that $\frac{\partial y_{ij}}{\partial w_{ij}}$, $\frac{\partial v_{ij}}{\partial w_{ij}}$, P_{ij}, and $\frac{\partial^2 v_{ij}}{\partial w_{ij}^s}$ are held constant across θ_j. Then $D\equiv D_1=D_2$, and we can simplify our first expression above to:

$$\frac{\lambda_Z\cdot\Big(\lambda_V E^+[v'']+\lambda_Z E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w^2_{\theta_i\theta_{HSES}}}\Big]\Big)}{D_1}-\frac{\lambda_Z\cdot\Big(\lambda_V E^+[v'']+\lambda_Z E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w^2_{\theta_i\theta_{LSES}}}\Big]\Big)}{D_2}$$
$$=\frac{\lambda_Z\cdot\lambda_Z}{D}\Big(E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta^2_{HSES}}}\Big]-E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta^2_{LSES}}}\Big]\Big)$$

This simplification is possible because we assume that $E^+[v'']$ and D are constant across θ_j, so the $\lambda_V E^+[v'']$ terms cancel out and $D_1=D_2=D$. Because of the concavity of U_i in Z_i, people with low $\bar{y}_i(n_i,\cdot)$ have high λ_Z. We will denote people with low $\bar{y}_i(n_i)$ as λ_Z^H and people with high $\bar{y}_i(n_i)$ as λ_Z^L, so that $\lambda_Z^H>\lambda_Z^L$ and $\lambda_Z^H\cdot\lambda_Z^H>\lambda_Z^L\cdot\lambda_Z^L$. Then:

$$\frac{\lambda_Z^H\cdot\lambda_Z^H}{D}\Big(E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta^2_{HSES}}}\Big]-E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta^2_{LSES}}}\Big]\Big)$$
$$-\frac{\lambda_Z^L\cdot\lambda_Z^L}{D}\Big(E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta^2_{HSES}}}\Big]-E^+\Big[\frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta^2_{LSES}}}\Big]\Big)>0$$

which is true when $\frac{\partial^2 y_{\theta_i\theta_{HSES}}}{\partial w_{\theta_i\theta_{HSES}}}>\frac{\partial^2 y_{\theta_i\theta_{LSES}}}{\partial w_{\theta_i\theta_{LSES}}}$. The inequality above implies that $\frac{\partial}{\partial w_{\theta_i\theta_{HSES}}}\big(-\frac{\partial w_{\theta_i\theta_{HSES}}}{\partial p^a}\big)-\frac{\partial}{\partial w_{\theta_i\theta_{LSES}}}\big(-\frac{\partial w_{\theta_i\theta_{HLSES}}}{\partial p^a}\big)$ is larger for people with lower $\bar{y}_i(n_i,\cdot)$. □

PROOF OF PROPOSITION 2:

For simplicity, we will use the following expression:

$$y'' = \frac{\partial^2 y_{ij}}{\partial w_{ij}^2}$$

Assume for analysis that $\frac{\partial y_{ij}}{\partial w_{ij}}$, $\frac{\partial v_{ij}}{\partial w_{ij}}$, P_{ij}, and $\frac{\partial^2 y_{ij}}{\partial w_{ij}^s}$ are held constant across θ_j. Then we can simplify equation **??** to:

$$\frac{\lambda_Z \cdot \left(\lambda_V E^+\left[\frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w^2_{\theta_i \theta_{HSES}}}\right] + \lambda_Z E^+[y'']\right)}{D_1} - \frac{\lambda_Z \cdot \left(\lambda_V E^+\left[\frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w^2_{\theta_i \theta_{LSES}}}\right] + \lambda_Z E^+[y'']\right)}{D_2}$$
$$= \frac{\lambda_Z \cdot \lambda_V}{D}\left(E^+\left[\frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w_{\theta_i \theta^2_{HSES}}}\right] - E^+\left[\frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w_{\theta_i \theta^2_{LSES}}}\right]\right)$$

This simplification is possible because we assume that $E^+[y'']$ and D are constant across θ_j, so the $\lambda_Z E^+[y'']$ terms cancel out and $D_1 = D_2 = D$. Because of the concavity of U_i in $V_i(a_{ij})$, people with low $\bar{v_i}(n_i)$ have high λ_V. We will denote people with low $\bar{v_i}(n_i)$ as λ_V^H and people with high $\bar{v_i}(n_i)$ as λ_V^L. Then, because Z_i and $V_i(a_{ij})$ are linearly additive in U_i, $\lambda_V^H > \lambda_V^L$ and $\lambda_Z \cdot \lambda_V^H > \lambda_Z \cdot \lambda_V^L$. Then:

$$\frac{\lambda_V^H \cdot \lambda_Z}{D}\left(E^+\left[\frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w_{\theta_i \theta^2_{HSES}}}\right] - E^+\left[\frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w_{\theta_i \theta^2_{LSES}}}\right]\right)$$
$$- \frac{\lambda_V^L \cdot \lambda_Z}{D}\left(E^+\left[\frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w_{\theta_i \theta^2_{HSES}}}\right] - E^+\left[\frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w_{\theta_i \theta^2_{LSES}}}\right]\right) < 0$$

which is true when $\frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w_{\theta_i \theta_{LSES}}} > \frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w_{\theta_i \theta_{HSES}}}$. The inequality above implies that $\frac{\partial}{\partial w_{\theta_i \theta_{HSES}}}\left(-\frac{\partial w_{\theta_i \theta_{HSES}}}{\partial p^a}\right) - \frac{\partial}{\partial w_{\theta_i \theta_{LSES}}}\left(-\frac{\partial w_{\theta_i \theta_{LSES}}}{\partial p^a}\right)$ is smallest for people with lower $\bar{v_i}(n_i)$. □

PROOF OF PROPOSITION 3:

Assume for analysis that $\frac{\partial y_{ij}}{\partial w_{ij}}$, $\frac{\partial v_{ij}}{\partial w_{ij}}$, and P_{ij} are held constant in θ_j. Then we can simplify equation **??** to:

$$\frac{\lambda_Z \cdot \left(\lambda_V E^+\left[\frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w^2_{\theta_i \theta_{HSES}}}\right] + \lambda_V E^+\left[\frac{\partial^2 y_{\theta_i \theta_{HSES}}}{\partial w^2_{\theta_i \theta_{HSES}}}\right]\right) - \lambda_Z \cdot \left(\lambda_V E^+\left[\frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w^2_{\theta_i \theta_{LSES}}}\right] + \lambda_V E^+\left[\frac{\partial^2 y_{\theta_i \theta_{LSES}}}{\partial w^2_{\theta_i \theta_{LSES}}}\right]\right)}{D} \tag{1}$$

Note that Equation 1 is non-zero and positive when $\frac{\partial^2 v_{\theta_i \theta_{HSES}}}{\partial w_{\theta_i \theta_{HSES}}} + \frac{\partial^2 y_{\theta_i \theta_{HSES}}}{\partial w_{\theta_i \theta_{HSES}}} > \frac{\partial^2 v_{\theta_i \theta_{LSES}}}{\partial w_{\theta_i \theta_{LSES}}} + \frac{\partial^2 y_{\theta_i \theta_{LSES}}}{\partial w_{\theta_i \theta_{LSES}}}$. This implies that $\frac{\partial}{\partial w_{\theta_i \theta_{HSES}}}\left(-\frac{\partial w_{\theta_i \theta_{HSES}}}{\partial p^a}\right) > \frac{\partial}{\partial w_{\theta_i \theta_{LSES}}}\left(-\frac{\partial w_{\theta_i \theta_{LSES}}}{\partial p^a}\right)$. □

Appendix D Invitation-Sending

Table D.1: Number of invitations respondent accompanied enumerator to send to...

	(1) Any	(2) Any	(3) Low-SES	(4) Low-SES	(5) High-SES	(6) High-SES
Inviter with High-SES Invitees	-0.090	-0.059			0.175***	-0.034
	(0.056)	(0.048)			(0.046)	(0.040)
Inviter with Low-SES Invitees	-0.038	0.049	0.251***	0.039		
	(0.047)	(0.045)	(0.043)	(0.039)		
Observations	1200	1200	800	800	800	800
Control Mean	0.527	0.527	0.253	0.253	0.275	0.275
Controls for Number of Type Invited	NO	YES	NO	YES	NO	YES

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: Chosen Guest Characteristics

	(1) Age	(2) Networks	(3) SES	(4) UCLA-3	(5) Roof	(6) Distance	(7) HH Power
High-SES	1.985***	0.395***	0.740***	-0.011	0.367***	0.009	-0.033
	(0.703)	(0.131)	(0.053)	(0.097)	(0.061)	(0.013)	(0.077)
Low-SES	-0.948	0.219	-0.799***	0.028	-0.470***	0.009	0.090
	(0.613)	(0.143)	(0.062)	(0.100)	(0.052)	(0.015)	(0.082)
Observations	974	974	974	967	1200	974	974
Controls for Average on List	NO	NO	NO	NO	NO	NO	NO
Control Mean	29.608	6.238	0.600	3.698	0.820	0.198	0.012
P-values							
Low-SES = High-SES	0.000	0.268	0.000	0.728	0.000	0.998	0.183

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table D.3: Chosen Guest Characteristics

	(1) Age	(2) Networks	(3) SES	(4) UCLA-3	(5) Roof	(6) Distance	(7) HH Power
Random + Voucher	1.016	0.075	0.177*	-0.157*	0.169*	-0.014	-0.082
	(0.815)	(0.145)	(0.095)	(0.093)	(0.087)	(0.015)	(0.090)
High-SES	1.938**	0.335*	0.793***	-0.110	0.506***	0.003	-0.085
	(0.854)	(0.180)	(0.079)	(0.131)	(0.089)	(0.018)	(0.078)
High-SES + Voucher	2.975***	0.507***	0.859***	-0.091	0.396***	-0.002	-0.074
	(0.900)	(0.185)	(0.077)	(0.127)	(0.078)	(0.015)	(0.101)
Low-SES	-0.603	0.283	-0.724***	0.003	-0.342***	-0.009	0.059
	(0.845)	(0.212)	(0.079)	(0.128)	(0.068)	(0.020)	(0.089)
Low-SES + Voucher	-0.296	0.255	-0.706***	-0.102	-0.433***	0.013	0.047
	(0.865)	(0.183)	(0.077)	(0.135)	(0.071)	(0.020)	(0.082)
Observations	974	974	974	967	1200	974	974
Controls for Average on List	NO	NO	NO	NO	NO	NO	NO
Control Mean	29.113	6.188	0.497	3.776	0.725	0.205	0.061
P-values							
High-SES: Voucher = No Voucher	0.098	0.277	0.153	0.857	0.232	0.737	0.892
: Low-SES: Voucher = No Voucher	0.665	0.893	0.756	0.378	0.070	0.260	0.873
Random + Voucher = High-SES + Voucher	0.031	0.007	0.000	0.536	0.012	0.432	0.944
Random + Voucher = Low-SES + Voucher	0.144	0.309	0.000	0.661	0.000	0.182	0.256

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table D.4: Chosen Guest Characteristics

	(1) Age	(2) Age	(3) Networks	(4) Networks	(5) SES	(6) SES	(7) UCLA-3	(8) UCLA-3	(9) Roof	(10) Roof	(11) Distance	(12) Distance	(13) HH Power	(14) HH Power
Voucher	0.780**	0.702*	0.076	0.143*	0.066	0.073*	-0.082	-0.070	-0.014	-0.007	0.001	0.000	-0.020	-0.030
	(0.398)	(0.360)	(0.085)	(0.082)	(0.046)	(0.042)	(0.060)	(0.055)	(0.047)	(0.044)	(0.008)	(0.007)	(0.049)	(0.046)
Observations	974	974	974	974	974	974	967	967	1200	1200	974	974	974	974
Controls for Average on List	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Control Mean	29.720	29.720	6.413	6.413	0.542	0.542	3.729	3.729	0.472	0.472	0.202	0.202	0.038	0.038

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table D.5: Reasons Chose First-Pick Guest

	(1) Generous	(2) Humble	(3) Warm	(4) Knowledgeable	(5) Connected	(6) Business	(7) Mother	(8) Hard-working	(9) Trust-worthy	(10) Respected	(11) Prayerful	(12) Marriage	(13) Needy
Random + Voucher	0.057	0.045	-0.019	-0.014	-0.137**	0.042	-0.008	0.031	0.027	0.024	-0.013	0.029	0.014
	(0.054)	(0.051)	(0.047)	(0.038)	(0.054)	(0.028)	(0.037)	(0.042)	(0.055)	(0.044)	(0.040)	(0.049)	(0.040)
High-SES	-0.013	0.055	0.097	0.071	-0.060	0.039	-0.014	0.012	-0.040	0.036	0.038	-0.033	-0.053
	(0.052)	(0.057)	(0.063)	(0.045)	(0.058)	(0.029)	(0.038)	(0.048)	(0.047)	(0.037)	(0.036)	(0.043)	(0.034)
High-SES + Voucher	0.067	0.084	-0.023	0.095**	-0.111**	0.020	-0.004	0.014	-0.061	0.020	0.064	-0.005	-0.041
	(0.054)	(0.051)	(0.046)	(0.046)	(0.055)	(0.032)	(0.031)	(0.044)	(0.049)	(0.042)	(0.043)	(0.044)	(0.033)
Low-SES	0.043	0.105*	0.002	-0.020	-0.068	0.006	0.027	-0.014	-0.025	0.018	0.043	-0.052	-0.007
	(0.054)	(0.058)	(0.052)	(0.036)	(0.060)	(0.031)	(0.037)	(0.050)	(0.043)	(0.037)	(0.042)	(0.037)	(0.035)
Low-SES + Voucher	0.100*	0.120**	0.126**	-0.003	-0.074	-0.010	-0.035	0.006	-0.042	-0.078**	0.048	0.002	-0.036
	(0.056)	(0.054)	(0.049)	(0.043)	(0.058)	(0.027)	(0.038)	(0.048)	(0.040)	(0.034)	(0.041)	(0.044)	(0.038)
Observations	974	974	974	974	974	974	974	974	974	974	974	974	974
Control Mean	0.259	0.392	0.488	0.139	0.717	0.060	0.175	0.181	0.211	0.157	0.151	0.199	0.127
P-values													
High-SES: Voucher = No Voucher	0.097	0.613	0.038	0.605	0.335	0.527	0.811	0.975	0.657	0.690	0.526	0.416	0.699
: Low-SES: Voucher = No Voucher	0.386	0.795	0.024	0.596	0.916	0.585	0.078	0.688	0.685	0.007	0.900	0.200	0.438
Random + Voucher = High-SES + Voucher	0.847	0.499	0.938	0.007	0.648	0.431	0.909	0.706	0.051	0.923	0.044	0.414	0.130
Random + Voucher = Low-SES + Voucher	0.418	0.168	0.011	0.784	0.280	0.084	0.491	0.607	0.188	0.005	0.143	0.542	0.161

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table D.6: Reasons Chose Guest (Average Across Guest)

	(1) Generous	(2) Humble	(3) Warm	(4) Knowledgeable	(5) Connected	(6) Business	(7) Mother	(8) Hard-working	(9) Trust-worthy	(10) Respected	(11) Prayerful	(12) Marriage	(13) Needy
Random + Voucher	0.017	0.006	-0.026	0.019	-0.044***	0.004	0.009	0.002	-0.012	-0.004	-0.018	0.014	0.005
	(0.015)	(0.014)	(0.018)	(0.013)	(0.015)	(0.009)	(0.011)	(0.013)	(0.015)	(0.012)	(0.013)	(0.014)	(0.013)
High-SES	-0.009	0.014	0.028*	0.024**	-0.026	0.005	-0.009	-0.009	-0.027*	-0.005	0.004	-0.005	-0.014
	(0.014)	(0.014)	(0.015)	(0.012)	(0.017)	(0.008)	(0.010)	(0.014)	(0.014)	(0.011)	(0.010)	(0.013)	(0.011)
High-SES + Voucher	0.019	0.032**	-0.005	0.025**	-0.037**	0.006	0.004	-0.008	-0.035**	-0.009	0.011	-0.008	-0.012
	(0.014)	(0.014)	(0.012)	(0.011)	(0.016)	(0.009)	(0.010)	(0.012)	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)
Low-SES	0.013	0.028*	0.002	0.004	-0.020	-0.001	0.007	-0.016	-0.016	-0.004	0.005	-0.013	-0.004
	(0.014)	(0.015)	(0.016)	(0.010)	(0.018)	(0.009)	(0.011)	(0.012)	(0.013)	(0.011)	(0.012)	(0.012)	(0.011)
Low-SES + Voucher	0.028**	0.031**	0.030*	0.007	-0.027	-0.003	-0.010	-0.015	-0.031**	-0.023**	0.003	-0.002	-0.008
	(0.014)	(0.013)	(0.017)	(0.012)	(0.018)	(0.008)	(0.010)	(0.011)	(0.012)	(0.011)	(0.010)	(0.013)	(0.011)
Observations	974	974	974	974	974	974	974	974	974	974	974	974	974
Control Mean	0.104	0.139	0.172	0.047	0.246	0.027	0.061	0.073	0.089	0.063	0.065	0.071	0.047
P-values													
High-SES: Voucher = No Voucher	0.059	0.232	0.026	0.929	0.507	0.918	0.256	0.947	0.515	0.690	0.504	0.738	0.812
: Low-SES: Voucher = No Voucher	0.296	0.832	0.093	0.762	0.688	0.821	0.076	0.926	0.210	0.057	0.832	0.343	0.680
Random + Voucher = High-SES + Voucher	0.868	0.085	0.183	0.648	0.694	0.807	0.653	0.416	0.097	0.732	0.023	0.025	0.135
Random + Voucher = Low-SES + Voucher	0.421	0.082	0.001	0.326	0.356	0.385	0.054	0.153	0.215	0.075	0.098	0.170	0.311

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E Downstream Outcomes

Table E.1: Occupation

	(1) Business	(2) New Business	(3) Business Copying	(4) Business Capital	(5) Agriculture	(6) Piecework	(7) Piecework: Idle Days	(8) Piecework Effort
High-SES × No Voucher	0.098***	0.076**	0.039**	0.098	-0.056	-0.065*	-0.572*	-0.200**
	(0.032)	(0.030)	(0.020)	(0.075)	(0.038)	(0.037)	(0.315)	(0.079)
High-SES × Voucher	0.090***	0.060**	0.039**	0.136*	-0.028	-0.021	0.391	-0.007
	(0.032)	(0.029)	(0.020)	(0.074)	(0.038)	(0.037)	(0.313)	(0.079)
Low-SES × No Voucher	0.011	-0.006	-0.016	0.006	-0.014	0.014	-0.062	-0.011
	(0.032)	(0.029)	(0.020)	(0.074)	(0.038)	(0.037)	(0.312)	(0.079)
Low-SES × Voucher	0.023	-0.003	-0.005	0.002	-0.021	0.028	0.143	0.002
	(0.032)	(0.030)	(0.020)	(0.075)	(0.038)	(0.037)	(0.315)	(0.079)
Random × No Voucher	0.052*	0.042	0.038*	0.026	-0.010	-0.017	-0.221	-0.087
	(0.032)	(0.030)	(0.020)	(0.074)	(0.038)	(0.037)	(0.314)	(0.079)
Random × Voucher	0.030	0.036	-0.003	-0.034	-0.014	0.028	0.036	-0.036
	(0.032)	(0.029)	(0.020)	(0.074)	(0.038)	(0.036)	(0.311)	(0.079)
Observations	1586	1586	1586	1587	1587	1587	1586	1586
Control Mean	0.179	0.129	0.048	-0.011	0.516	0.335	1.808	0.028

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Savings and Income

	(1) VSLA	(2) ROSCA	(3) Total Loans	(4) Any Formal Loan	(5) Loans % Formal	(6) Earned Myself	(7) Earned Total	(8) My Money
High-SES × No Voucher	0.014	-0.017	0.016	-0.023	0.093**	-0.003	-0.038	312.873
	(0.032)	(0.027)	(0.507)	(0.035)	(0.041)	(0.016)	(0.036)	(485.875)
High-SES × Voucher	0.061*	-0.004	0.093	0.029	0.030	0.028*	0.039	729.840
	(0.032)	(0.027)	(0.500)	(0.035)	(0.038)	(0.016)	(0.036)	(480.468)
Low-SES × No Voucher	-0.000	-0.029	-0.149	-0.047	0.012	-0.002	-0.050	-39.796
	(0.032)	(0.027)	(0.499)	(0.035)	(0.041)	(0.016)	(0.036)	(482.897)
Low-SES × Voucher	-0.042	0.001	0.254	0.019	0.041	0.001	-0.021	-195.266
	(0.032)	(0.027)	(0.505)	(0.035)	(0.038)	(0.016)	(0.036)	(484.827)
Random × No Voucher	0.004	-0.058**	0.389	-0.013	0.060	0.014	0.035	1016.368**
	(0.032)	(0.027)	(0.503)	(0.035)	(0.040)	(0.016)	(0.036)	(488.744)
Random × Voucher	0.008	-0.004	0.297	0.025	0.085**	0.004	-0.038	218.921
	(0.032)	(0.027)	(0.498)	(0.035)	(0.038)	(0.016)	(0.036)	(480.360)
Observations	1586	1586	1286	1286	448	1586	1586	1543
Control Mean	0.419	0.159	2.439	0.198	0.338	0.159	0.446	4547.668

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table E.3: Consumption

	(1) Own Maize	(2) Maize KGs	(3) Kernels KGs	(4) Flour KGs	(5) Maize % Flour	(6) Meat Past Month	(7) Protein Past Month	(8) Daily Meals
High-SES × No Voucher	-0.019	-1.133	0.783	-2.406	-0.036	0.078	0.232	-0.350
	(0.034)	(1.992)	(6.571)	(1.594)	(0.034)	(0.151)	(0.331)	(0.227)
High-SES × Voucher	-0.001	0.212	1.228	-1.304	-0.020	0.978***	1.153***	-0.222
	(0.033)	(1.982)	(6.541)	(1.585)	(0.033)	(0.150)	(0.329)	(0.225)
Low-SES × No Voucher	-0.020	-1.927	-4.517	-3.506**	-0.010	-0.005	-0.038	-0.456**
	(0.033)	(1.981)	(6.531)	(1.586)	(0.035)	(0.150)	(0.328)	(0.225)
Low-SES × Voucher	-0.035	-2.658	-6.723	-0.346	0.034	0.975***	0.956***	-0.310
	(0.034)	(1.988)	(6.559)	(1.591)	(0.034)	(0.151)	(0.331)	(0.226)
Random × No Voucher	0.050	4.658**	15.181**	0.340	-0.083**	0.421***	1.008***	-0.377*
	(0.034)	(1.986)	(6.543)	(1.588)	(0.034)	(0.150)	(0.330)	(0.226)
Random × Voucher	-0.042	1.209	5.685	-0.122	-0.030	0.964***	1.391***	-0.225
	(0.033)	(1.972)	(6.505)	(1.576)	(0.033)	(0.149)	(0.328)	(0.224)
Observations	1586	1586	1586	1586	1219	1586	1586	1586
Control Mean	0.311	18.424	43.194	22.797	0.663	1.717	4.770	2.648

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table E.4: Maize Stores (Enumerator Verified)

	(1) Enumerator Verified	(2) Maize KGs	(3) Kernels KGs	(4) Flour KGs	(5) Maize % Flour
High-SES × No Voucher	-0.029	-0.732	3.501	-4.396**	-0.065
	(0.035)	(2.528)	(8.346)	(1.989)	(0.040)
High-SES × Voucher	0.005	0.501	1.683	-2.387	-0.045
	(0.034)	(2.495)	(8.244)	(1.966)	(0.039)
Low-SES × No Voucher	0.009	0.093	2.748	-5.075***	-0.039
	(0.035)	(2.502)	(8.256)	(1.961)	(0.040)
Low-SES × Voucher	0.025	-2.341	-4.342	-1.698	0.033
	(0.035)	(2.473)	(8.172)	(1.945)	(0.039)
Random × No Voucher	-0.005	5.148**	19.284**	-0.454	-0.107***
	(0.035)	(2.504)	(8.267)	(1.979)	(0.041)
Random × Voucher	0.022	0.109	1.692	0.087	-0.000
	(0.035)	(2.447)	(8.088)	(1.929)	(0.038)
Observations	1618	1131	1131	1131	900
Control Mean	0.663	18.424	43.194	22.797	0.663

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table E.5: Psychological Well-being

	(1) Index	(2) CESDR-10 Score	(3) Depression	(4) UCLA-3 Score	(5) Lonely	(6) Female Empowerment	(7) Perceived Acceptance	(8) Distance	(9) Told about Husband	(10) Still Married
High-SES × No Voucher	0.102	-0.301	-0.024	-0.069	-0.027	0.009	0.050	-0.026	-0.018	0.013
	(0.085)	(0.407)	(0.034)	(0.084)	(0.022)	(0.073)	(0.074)	(0.077)	(0.019)	(0.016)
High-SES × Voucher	-0.150*	0.396	0.035	0.093	0.045**	-0.074	0.037	-0.124	-0.021	0.000
	(0.084)	(0.403)	(0.034)	(0.083)	(0.022)	(0.073)	(0.073)	(0.077)	(0.019)	(0.016)
Low-SES × No Voucher	-0.108	0.526	0.053	0.024	0.017	-0.033	0.059	-0.095	-0.034*	0.013
	(0.084)	(0.403)	(0.034)	(0.083)	(0.022)	(0.072)	(0.073)	(0.077)	(0.019)	(0.015)
Low-SES × Voucher	-0.018	0.042	-0.001	-0.040	0.031	-0.085	0.122*	-0.125	-0.007	0.011
	(0.085)	(0.404)	(0.034)	(0.085)	(0.023)	(0.073)	(0.073)	(0.077)	(0.019)	(0.016)
Random × No Voucher	-0.029	0.327	0.008	-0.026	0.014	0.003	0.164**	-0.054	0.007	0.010
	(0.083)	(0.405)	(0.034)	(0.083)	(0.022)	(0.073)	(0.073)	(0.077)	(0.019)	(0.016)
Random × Voucher	-0.093	0.469	0.061*	-0.014	0.027	-0.021	-0.052	-0.029	-0.008	-0.012
	(0.084)	(0.401)	(0.034)	(0.083)	(0.022)	(0.072)	(0.073)	(0.077)	(0.019)	(0.015)
Observations	1434	1587	1587	1434	1434	1586	1586	1586	1586	1092
Control Mean	0.000	7.055	0.297	3.513	0.058	-0.005	-0.049	0.399	0.068	0.966

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table E.6: Networks

	(1) Network Size	(2) New Friends	(3) Old Friends	(4) Dropped Friends	(5) Any Iron Sheets	(6) All Iron Sheets	(7) % Iron Sheets	(8) % Hus.' Rels.
Random × No Voucher	0.159	0.114	0.025	-0.040	0.042**	-0.017	-0.010	-0.006
	(0.123)	(0.114)	(0.106)	(0.107)	(0.021)	(0.016)	(0.012)	(0.011)
Random × Voucher	0.105	0.112	0.049	-0.062	0.006	-0.012	-0.004	0.005
	(0.123)	(0.113)	(0.105)	(0.107)	(0.021)	(0.016)	(0.012)	(0.011)
High-SES × No Voucher	-0.050	-0.006	-0.018	0.032	0.004	-0.005	-0.008	-0.007
	(0.124)	(0.115)	(0.107)	(0.108)	(0.021)	(0.016)	(0.012)	(0.011)
High-SES × Voucher	-0.043	-0.072	0.078	-0.089	-0.011	0.041***	0.019	-0.010
	(0.123)	(0.114)	(0.105)	(0.107)	(0.021)	(0.016)	(0.012)	(0.011)
Low-SES × No Voucher	-0.040	-0.055	0.016	-0.032	0.035*	0.022	0.005	-0.010
	(0.123)	(0.114)	(0.105)	(0.107)	(0.021)	(0.016)	(0.012)	(0.011)
Low-SES × Voucher	-0.164	-0.044	-0.090	0.099	-0.014	0.007	-0.013	0.003
	(0.124)	(0.114)	(0.106)	(0.108)	(0.021)	(0.016)	(0.012)	(0.011)
Observations	1586	1586	1586	1586	1586	1586	1586	1586
Control Mean	6.096	1.571	4.525	1.775	0.864	0.056	0.415	0.090

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$