Risk Preferences and Risk Pooling in Networks: Theory and Evidence from Community Detection in Ghana

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Abstract

When risk preferences are heterogeneous, pooling covariate risk can lead to welfare improvements by shifting correlated shocks from more risk averse to less risk averse agents in exchange for a premium. However, the ability to pool covariate risk in this way depends crucially on whether agents prefer to share risk with others who have similar risk preferences. Do agents assortatively match on risk preferences? To investigate this question, I build a theoretical model of covariate risk pooling with heterogeneous risk aversion. I use rich data from four villages in southern Ghana to construct a bilateral risk sharing network and community detection algorithms to detect risk pooling communities, which bound the scope of risk pooling. Using econometric models of network formation, I estimate that individuals prefer to assortatively match in risk sharing networks. But, in detected communities the magnitude of assortative matching falls considerably. I compare the allocation of agents in communities to three benchmarks, including an optimal and worst-case scenario. In terms of assorative matching, I find that the observed networks deviate only slightly from optimal networks for this form of risk pooling.

Keywords: Risk Pooling, Network Formation, Assortative Matching, Risk Preferences, Community Detection

JEL Codes: O12, 016, 017, L14

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1 Introduction

Despite the riskiness of life in the developing world, formal financial markets, including insurance markets, are often missing (Mccord et al., 2007). In the absence of formal insurance markets, informal risk sharing, mediated through social networks, is a common and important method of managing risk. The past decade has seen a proliferation of financial products. As these formal financial markets, including savings, microfinance, and insurance markets, enter rural economies they tend to crowd out informal risk sharing (Banerjee et al., 2018; Comola and Prina, 2020; Cecchi et al., 2016; Dizon et al., 2019). The net welfare effects of access to this diversity of new financial products is therefore ambiguous and may be shaped importantly by unintended behavioral responses of target beneficiaries.

In this paper, I explore a little studied version of risk pooling, where less risk averse agents take on risk from more risk averse agents in exchange for a premium. The classic story of informal risk sharing is of two people who are subject to uncorrelated shocks. This includes risks like illness, loss of employment, and theft: if you lose your job, I insure you; If I lose my job, you insure me. This story has long been studied as a way to smooth this idiosyncratic risk. Indeed, the evidence is often consistent with a high degree of idiosyncratic risk sharing (Townsend, 1994; **?**). In contrast, sharing of correlated risks like output price and weather has received much less attention. Despite this, when risk preferences are heterogeneous, sharing covariate risk can lead to welfare improvements by shifting covariate risks from more risk averse to less risk averse agents in exchange for a premium (Chiappori et al., 2014). In this story of informal risk sharing, in a bad year the less risk averse agent takes the hit. In a good year, they receive the prize; and in all years they are rewarded by the more risk averse agent for taking on this risk.

This story, however, depends critically on the proximity of less and more risk averse agents in risk sharing networks. Homophily, or the preference to connect to those similar to oneself, is a common feature of social and economic networks (Miller McPherson et al., 2001). In the setting of risk sharing, Attanasio et al. (2012) demonstrates that individuals prefer to share risk with those who have similar risk preferences in a lab in field setting. This pattern of *assortative matching* on risk preferences arises as a barrier to this type of risk sharing. This leads me to the question of interest: given the degree of assorative matching on risk preferences found in real world risk sharing networks, how good of insurance can covariate risk sharing deliver? Empirically, I study this question by asking if individuals form connections with others who have similar or different risk preferences. Using models of network formation and a theoretical model of risk pooling, I estimate the degree to which agents match with those who have similar risk preferences and quantify the impacts to welfare from this aspect of network structure. To measure the degree of assorative matching on risk preferences, I apply dyadic regression and Subgraph Generation Models (SUGMs) to rich microdata featuring income shocks, networks, and risk preferences from a survey in four villages in rural southern Ghana. This setting features prominent correlated income risk and the data includes a detailed social networks module, and a set of hypothetical gambles. I look carefully at networks and use two main measures of the risk pooling network. First, I connect people who have exchanged gifts in the past and trust each other in a bilateral risk sharing network. Second, I arrange individuals in risk pooling groups using *community detection*, clustering methods which are sensitive to the details of networks (Newman, 2011). I argue this measure of risk pooling groups accounts for the possible scope of risk pooling in networks (i.e., the relevant set of individuals). For risk preferences, in order to match the theory as closely as possible, I back out coefficients of absolute risk aversion using these hypothetical gambles.

To translate these estimates into concrete welfare estimates, I construct a theoretical model of optimal risk pooling in a village setting. This model resides in a subvillage group setting from a baseline of full idiosyncratic risk pooling and features agents with high and low risk aversion who will be assigned to one of two risk pooling groups. According to this model, optimal risk pooling happens when the composition of the groups reflects the composition of the village. For example, if the village is made up of 50% less risk averse individuals, you would prefer each group to also be made up of 50% less risk averse individuals. This result implies that optimal risk pooling should feature no assortative matching on risk preferences.

Using dyadic regression, I estimate that individuals do prefer to assortatively match on risk preferences in the risk sharing network. That is, they prefer to match with individuals who have a similar degree of risk aversion. These results are qualitatively robust to controlling for a large set of variables related to other aspects of homophily and popularity, though the magnitude of estimates falls.[1] Moreover, this tends to be driven by connections between family members, though I do not rule out that family might be proxying for other aspects of dyadic affinity. In addition, I estimate a set of SUGMs, which yields similar results (Chandrasekhar and Jackson, 2018). This model allows for further exploration of who matches with whom: I find that assortative matching is driven by less risk averse individuals, who tend to have higher degree overall and harbor a preference to connect to their own type. When I treat risk pooling communities as the relevant unit of risk sharing at the subvillage level, however, I do not find evidence of assortative matching on risk preferences using dyadic regression. Likewise, when estimating the SUGMs, I find that the magnitude of assortative matching is reduced as compared to the risk sharing network. In other words, risk pooling communities feature more diverse preferences than bilateral risk sharing relationships.

What are the welfare impacts of this degree of assortative matching? I divide individuals into more and less risk averse types and quantify the welfare implications of the allocation of types in communities. To do this, I simulate four scenarios: (A) an optimal scenario, (B) a community scenario, (C) the bilateral scenario, and (D) a worst case scenario. (A) and (D) are determined by the theoretical model derived earlier, while (B) and (C) derive from empirical estimates. Whereas the community scenario (B) takes the degree of assortative matching estimated from the risk pooling community estimates and the scope of risk pooling as detected, the bilateral scenario takes estimates of assorative matching from the risk sharing network and places these within the scope measured by the detected communities. I find

[1] These controls include demographics, occupation, education, and (family) network centrality

substantial differences between the optimal and worst case scenario, with the community and bilateral scenarios both falling close to optimal. First, I find that the observed networks tend to be close to optimal networks already. If 0% is the worst case scenario, and 100% is the best case scenario, the observed networks are close to 75%. As you might expect, the more diverse risk pooling groups function better for covariate risk pooling than the bilateral networks. However, if I use full covariate insurance as a benchmark, even the optimal scenario has losses equal to 16.5% of per capita consumption. While individuals may be able to do well with the tools they are given, there are still large gains to be had in improved risk management.

This work contributes to the understanding of network formation in the context of risk sharing. First, the results mirror those from earlier studies of assorative matching on risk preferences. In particular, the results from dyadic regression using the risk sharing network as an outcome strongly mirror those of Attanasio et al. (2012), albiet in a different country context and with a different research design. Beyond replicating these results, the current work both provides evidence of assortative matching on risk preferences in real world risk sharing relationships. This is consistent with models of assortative matching in the preseence of idiosyncratic risk sharing (Jaramillo et al., 2015; Wang, 2015; Attanasio et al., 2012). Second, this paper contributes to the understanding of assortative matching as a barrier to covariate risk sharing. Despite the fact that the scope of risk pooling measured here is significantly smaller than the village level, individuals tend to have diverse enough networks that informal covariate risk pooling, like that described in Chiappori et al. (2014) is feasible in this context.

2 Background

2.1 Related Literature

2.1.1 Covariate and Idiosyncratic Risk Sharing

Formal insurance markets are often missing in developing economies (Mccord et al., 2007). In the absence of formal insurance markets, informal risk sharing, mediated through social networks, helps fill this void (Fafchamps and Lund, 2003; Fafchamps, 2008). In theory, covariate risk sharing has great potential to benefit those who face risk (and lack formal insurance markets). Using panel data from Thailand, Chiappori et al. (2014) structurally estimates risk preferences in villages when risk sharing arrangements are complete. The current work first differs in modeling approach by using constant absolute risk aversion preferences as opposed to constant relative risk aversion. This choice relates more the the convenience of presenting welfare results. The solution of the two modeling approaches share an intuition: less risk averse agents might take on more covariate risk in exchange for some increase in consumption over the long term. In their model, individuals who have risk preferences near to risk neutral make a market in taking on additional covariate risk. This intuition is further shared by the model in Wang (2015). More substantially, the current work relaxes the assumption of covariate risk pooling at the village level to get at the relationship between network structure, network formation and the viability of covariate risk sharing.

The covariate risk sharing in the current work is distinct from inter-village risk sharing which can also help cope with covariate risk. For example Mobarak and Rosenzweig (2012) finds correlated (e.g., rainfall) shocks are insured at the *jati* (subcaste) level in India. These *jati*, however, span villages and this can account for this fact. Additionally, the line between covariate and idiosyncratic shocks has blurred with mobile financial technologies. The rapid spread of mobile money payment systems has reduced transaction costs for transferring money long distances (Jack and Suri, 2014). For those connected to mobile money, canonical covariate shocks (drought, flooding, earthquakes) can become idiosyncratic (Blumenstock et al., 2016; Riley, 2018).

2.1.2 Assortative Matching in Risk Sharing Networks

A tension fundamental to covariate risk sharing is between the observed propensity for *homophily* in risk sharing networks and the need for diversification of risk and risk preferences. Homophily – or the principle that similarity breeds connection – has long been studied in social networks more broadly (Miller McPherson et al., 2001). A number of theoretical papers make predictions about assortivity in risk sharing networks. In the context of risk sharing, Attanasio et al. (2012) constructs a model of network formation that predicts those with similar risk aversion tend to connect in a network formation process. Wang (2015) also builds a model of risk sharing with heterogeneity in risk preferences and predicts assortative matching in risk preferences under certain conditions. However, agents are also predicted to match assortatively on other dimensions. For example, agents are predicted to assortatively match on their level of riskiness (e.g., income shock variance) (de Weerdt, 2002; Jaramillo et al., 2015; Gao and Moon, 2016).

Attanasio et al. (2012) uses a risk pooling experiment to test for assortative matching in 70 municipalities in Colombia. In this study, the authors measure risk aversion by offering a set of gambles. Then they give their experimental subjects the ability to form risk pooling groups to pool risk. They find close friends and relatives match assortatively on risk attitudes, whereas less familiar dyads tend not to match at all. My results qualitatively mirror these results, providing a scientific replication of the results of Attanasio et al. (2012) using observational data from Ghana. Notably, the conditions for assortative matching in Wang (2015) hold in this experiment. In addition, Fafchamps and Gubert (2007) finds evidence of geographic assortative matching in risk sharing networks (though this is likely correlated with kinship). Likewise, de Weerdt (2002) finds that matching in a Tanzanian village is driven by geography, wealth, religious affiliation, clan membership, and kinship.

2.1.3 The Scope of Risk Pooling

The *scope* of risk pooling is the various set of individuals a given individual might benefit from pooling risk with. Very often the implied scope of risk pooling is all other agents in the village, as much of the literature takes the assumption of a village clearinghouse. For example, Townsend (1994) develops a model to test for the presence of efficient risk sharing at the village level. Contrary to this assumption of village level risk sharing, transfers tend to occur over reciprocal, bilateral relationships (Fafchamps and Lund, 2003; de Weerdt and Dercon, 2006; Blumenstock et al., 2016). Here the scope of risk pooling is only the individuals directly connected to each other with each connected pair forming a risk pool. Specific contexts allow us to observe the scope of informal or quasi-formal risk pooling groups, including mutual fire insurance in Andorra (Cabrales et al., 2003), funeral societies in Ethiopia and Tanzania (Dercon et al., 2006), and kinship groups in Malawi (Fitzsimons et al., 2018). However, these contexts tend to be the exception. In general, informal insurance groups do not coincide with the village.

What is the relevant scope of risk pooling? Absent these quasi-formal groups, is it only to ones (network) neighbors, or do some members of village beyond neighbors contribute to risk pooling? Theory suggests reasons for relevant individuals to lie beyond the network neighborhood. First, Ambrus et al. (2014) models the effect of risk sharing network structure on *ex post* consumption risk sharing. After shocks have been realized, they hypothesize the emergence of risk sharing islands where consumption is smoothed. The scope of risk sharing extends beyond the immediate network neighborhood. These risk sharing islands differ from the risk pooling communities described later in this paper, but are conceptually related. In particular, risk pooling communities map the *ex ante* structure of village risk sharing networks while risk sharing islands map *ex post* consumption smoothing conditional on existing networks and realized shocks. Risk sharing islands arise *ex post* where risk pooling communities exist *ex ante*. Second, Bourlès et al. (2017), model altruism in networks and find that intermediaries are important to flows of transfers through networks when networks are intransitive.

Empirically, Jackson et al. (2012) emphasizes the role of network *support* in favor exchange (including risk sharing transfers), i.e., that stable gift giving relationships will have a third person connected to both "supporting" the relationship. In contrast the theoretical results, this might imply a restriction to the network neighborhood to only those individuals featuring support. Fitzsimons et al. (2018) predicts that larger risk sharing groups will result in worse risk sharing and finds evidence for this using data from rural Malawi. de Weerdt and Dercon (2006) finds that first order connections matter for illness related risk sharing, but second order connections do not. However, in co-current work, I find that detected communities can help predict the decision to join an experimental risk pooling group, even when controlling for many other network features (Putman, 2020). This empirical work motivates the use of community detection algorithms.

2.1.4 Risk-Shifting Contracts: Sharecropping and Rental Markets

As is the case with idiosyncratic risk pooling, the theory is often mum about what kinds of transactions should account for covariate risk pooling. Some more concrete notions of arrangements can be found in the literature on sharecropping, and risk management which emphasizes sharecropping as way for a more risk averse renter to pass risk to their less risk averse landlord (Stiglitz, 1974; Braverman and Stiglitz, 1986). As is noted in Allen and Lueck (1995), for this set-up to match with the model presented in Section 3, renters need be more risk averse than landlords. Sharecropping, for it's part, is relatively common in the context at hand, accounting for about about 50% of contracts (Goldstein and Udry, 2008).

2.2 Graphs and Risk Sharing Networks

Throughout this paper, I will draw on graph theory to describe intuition, formalize intuition and visually represent risk sharing networks. A graph g is a set of *nodes* and an *edgelist* (which naturally contains *edges*). I refer to these nodes and edges by their subscripts. I subscript nodes by i. For edges, I use the combination of subscripts i and j to refer to that edge: if there is a connection between i and j, I say $ij \in g$, hence ij is in the edgelist. An adjacency matrix represents these nodes and edges in an $n \times n$ matrix $\mathbf{A} = \mathbf{A}(g)$. For the scope of this paper, I work with unweighted and undirected graphs, choosing to work with reciprocal relationships. Thus $a_{ij} = 1$ if $ij \in g$ and 0 if not. The adjacency matrix is also symmetric: $a_{ij} = a_{ji}$ for all i, j. The diagonal $a_{ii} = 0$ by construction.

Nodes and edges go by many other names. In the case of risk sharing, nodes represent agents and edges represent the social connections between those agents. I will use "agents" and "individuals" interchangeably when referring to nodes in the network. Likewise, I will use "links" and "connections" interchangeably when referring to edges. *Dyads* are not interchangeable, however: dyads are all possible combinations ij regardless of whether that edge exists in the network.

How do risk sharing networks relate to risk sharing arrangements? I take the view that risk sharing arrangements (and by extension, risk pooling arrangements) are *ex ante* informal contracts specifying transfers based on *ex post* states of the world. Given the complexity of such a contract, the edge itself does not tell the story of the risk sharing arrangement happening over that edge. For parameterized contracts, however, these parameters can be listed as edge characteristics. Depending on whether the risk sharing network is *ex ante* or *ex post*, these social connections may reflect agreements of transfers or past transfers (or some mix of the two).

Some node level measures I will use are *neighborhood* and *degree*. An agent i's *neighborhood* is all agents j such that $ij \in g$. An agent i's *degree* is the size of agent i's neighborhood. Degree is computed $d(i) = \sum_{j=1}^{n} a_{ij}$. On the network level, some measures of network structure are *density* and *clustering*. The *density* of a network is the total number of connections divided by the number of potential connections. The clustering coefficient of a network takes (three times) the number of triangles and divides it by the potential number of triangles.

3 Theoretical Model

This model considers a risk-neutral planner who seeks to construct two risk pooling communities in a village to maximize expected utility within the village. Here I leave aside community size and its impact on community composition and focus on optimal community composition. In this case, I think about community composition with regard to risk aversion, with relatively less and more risk averse individuals. I set up this problem in two steps. First, I characterize how risk is pooled in a community according to its composition. Second, using the solutions and value functions from the first optimization problem, I write a planners problem maximizing aggregate expected utility of consumption in a village with communities conditional on the composition of those communities.

3.1 Risk Sharing in Communities

To model risk sharing in communities, I start from a baseline of perfect idiosyncratic risk sharing. This means that all shocks that are above and below a villager's mean income are smoothed to their mean income (I will assume these are zero for the purposes of this problem). After this set of transfers takes place, a round of risk shifting takes place. Less risk averse individuals may take on more of covariate risk. This covariate risk derives from both the average idiosyncratic shock, which in general is not zero, and the (perfectly correlated) covariate shock. More risk averse agents are able to take on less of the covariate risk over time, shifting them on to less risk averse individuals. However, less risk averse individuals are still risk averse, so they require some compensation for the risk they take on. Thus, recurring transfers are made to these individuals regardless of the covariate shock.

3.1.1 Setup

Suppose a community of fixed size N. Villager i has exponential utility functions with coefficient of absolute risk aversion η_i.

$$u_i(c_i) = \frac{1 - e^{-\eta_i c_i}}{\eta_i}$$

However, suppose there are low and high risk aversion households, where type and indexed by $\ell = 1, 2$. Then I assume $\eta_2 > \eta_1 > 0$. N_ℓ is number of individuals of type ℓ, and $p = N_1/N$ characterizes the composition of the group. All households face a perfectly correlated shock, $\tilde{y}_v$ and an idiosyncratic shock $\tilde{y}_i$. Risk is symmetric between households and between types: Household level shocks, $\tilde{y}_i \sim^{\text{iid}} N(0, \sigma^2)$ and type level shocks $\tilde{y}_v \sim^{\text{iid}} N(0, \nu^2)$. Income for agent i and type ℓ is computed $y_{\ell i} = \tilde{y}_i + \tilde{y}_v$. Taking account of the risk sharing process, I write the consumption of household i of type ℓ as a weighted sum of the idiosyncratic and covariate shock in the community. For type $\ell = 1, 2$,

$$c_{1i} = \left(\frac{\theta}{p}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right) - \lambda_{1i} \quad \text{and} \quad c_{2i} = \left(\frac{1-\theta}{1-p}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right) - \lambda_{2i}.$$

The proportion of covariate risk that is borne by the less risk averse individuals in the community is regulated by the parameter $\theta \in [0, 1]$. When $\theta = 1$, all risk is taken on by less risk averse individuals, when $\theta = p$, risk is shared equally among all members of the community (i.e., only idiosyncratic risk is pooled), and when $\theta = 0$ all risk is taken on by more risk averse households. Conversely, $\lambda_{\ell i}$ regulates the recurring transfers from the more risk averse to the less risk averse. Thus, it is the case that the aggregate transfer into the pot exceeds the aggregate transfer out: $-N_1\lambda_{1i} \leq N_2\lambda_{2i}$. Due to the exponential utility function and normal distribution of shocks, I am able to represent expected utility as a mean-variance decomposition

$$E(U(c_{\ell i})) = E(c_{\ell i}) - \frac{\eta_{\ell i}}{2} Var(c_{\ell i})$$

I will refer to the special case of $EU_0 = E(U(c_1 i|\theta = p)))$, which simply describes the utility from idiosyncratic risk sharing in absence of risk sharing.

3.1.2 Optimization Problem

The planner maximizes expected utility of less risk averse agents subject to several constraints.

$$\max_{\lambda_1,\lambda_2,\theta} E(U_1(c_{1i})) \tag{1}$$

$$\text{subject to} \qquad EU_0 \leq E(U(c_{2i})) \tag{2}$$

$$c_{1i} = \left(\frac{\theta}{p}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right) - \lambda_{1i} \tag{3}$$

$$c_{2i} = \left(\frac{1-\theta}{1-p}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right) - \lambda_{2i} \tag{4}$$

$$0 \leq p\lambda_1 + (1-p)\lambda_2 \tag{5}$$

Constraint 2 is an incentive compatibility constraint: more risk averse agents cannot being worse off than in the case where they only perfectly pool idiosyncratic risk. Constraints 3 and 4 serve as individual budget constraints for each type, and finally 5 serves to ensure feasibility of the recurring transfers.

3.1.3 Solutions and Value Functions

How much covariate risk is shifted to the less risk averse agents? Recall, if $\theta = 1$, all covariate risk shifts to less risk averse individuals, and if $\theta = p$, the baseline of perfect idiosyncratic risk sharing is maintained.

$$\theta^*(p, \eta_1, \eta_2) = \frac{p\eta_2}{(1-p)\eta_1 + p\eta_2} \tag{6}$$

Since $\eta_2 > \eta_1$, $\theta^* > p$. This means some degree of covariate risk is shifted to less risk averse individuals. Likewise, unless $\eta_1 = 0$ (I assumed it doesn't) or $p = 1$ not all risk is taken on by the less risk averse. This brings us to an important result of the model: group composition matters for the degree of risk sharing. What are more risk averse agents willing to pay to shift risk away? Since λ_2^* is paid into the community pot, Type 2's willingness to pay depends on their own risk aversion, type 2's risk aversion, and group composition

$$\lambda_2^*(p, \eta_1, \eta_2) = -\frac{\eta_2}{2}\left(1 - \frac{\eta_1^2}{((1-p)\eta_1 + p\eta_2)^2}\right) \tag{7}$$

where the expression in parentheses lies between 0 and 1. Because risk is symmetric in this model, the transfer does not depend on covariate risk. Presumably, were this not the case, it would appear in the above solutions. Finally, type 1 will maximize their utility and hence the payments they receive from type 2. I can write λ_1^* by converting type 2's willingness to pay into type 1's average payment:

$$\lambda_1^*(p, \eta_1, \eta_2) = -\left(\frac{1-p}{p}\right)\lambda_2^*(p). \tag{8}$$

Once I have these solutions I am able to compute the value functions I will use in order to solve the planner's problem. These are

$$\begin{aligned} V_1(p, \eta_1, \eta_2) = & \frac{\eta_1}{2}\left(\frac{1-p}{p}\right)\left(1 - \left(\frac{\eta_1}{(1-p)\eta_1 + p\eta_2}\right)^2\right) \\ & - \frac{\eta_1}{2}\left(\frac{\eta_2}{(1-p)\eta_1 + p\eta_2}\right)^2\left(\frac{\sigma^2}{n} + \nu^2\right) \end{aligned} \tag{9}$$

$$V_2(p, \eta_1, \eta_2) = \frac{\eta_2}{2}\left(1 + \left(\frac{\eta_1}{(1-p)\eta_1 + p\eta_2}\right)^2\left(1 + \left(\frac{\sigma^2}{n} + \nu^2\right)\right)\right) \tag{10}$$

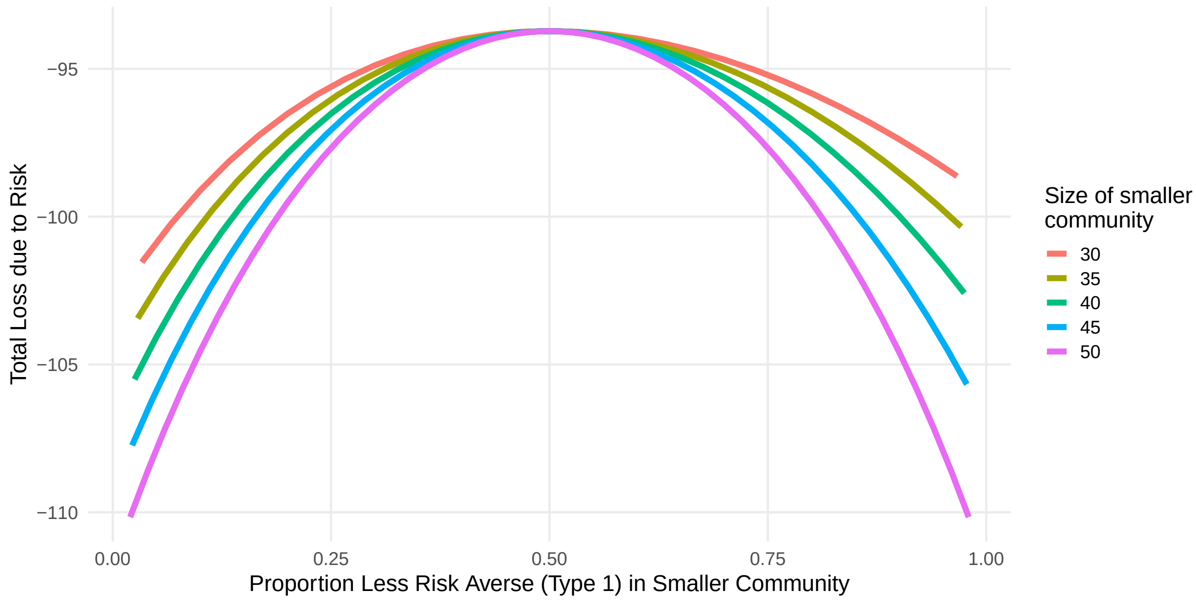


Figure 1: Optimal Allocation of Types Between Unequally Sized Communities

3.2 Planner's Problem

3.2.1 Setup

The risk neutral planner seeks to maximize aggregate expected utility of consumption conditional on the composition of communities. There are two communities, $g = A, B$. I will update the notation from the first stage slightly. For a given community g, N_g is the community size and $N_A + N_B = N$. Then $N_{g\ell}$ is the number of individuals of type ℓ in community g and $p_{g\ell} = \frac{N_{g\ell}}{N_g}$.

3.2.2 Optimization Problem

I state the planner's problem as follows:

$$\max_{N_{1A}} \quad N_{A1}V_1(p_{A1}) \ + \ N_{A2}V_2(p_{A1}) \ + \ N_{B1}V_1(p_{B1}) + N_{B1}V_2(p_{B1}) \tag{11}$$

$$\text{subject to} \quad N_\ell = \ N_{A\ell} + N_{B\ell}, \quad \ell = 1, 2 \tag{12}$$

$$N_g = \ N_{g1} + N_{g2}, \quad g = A, B \tag{13}$$

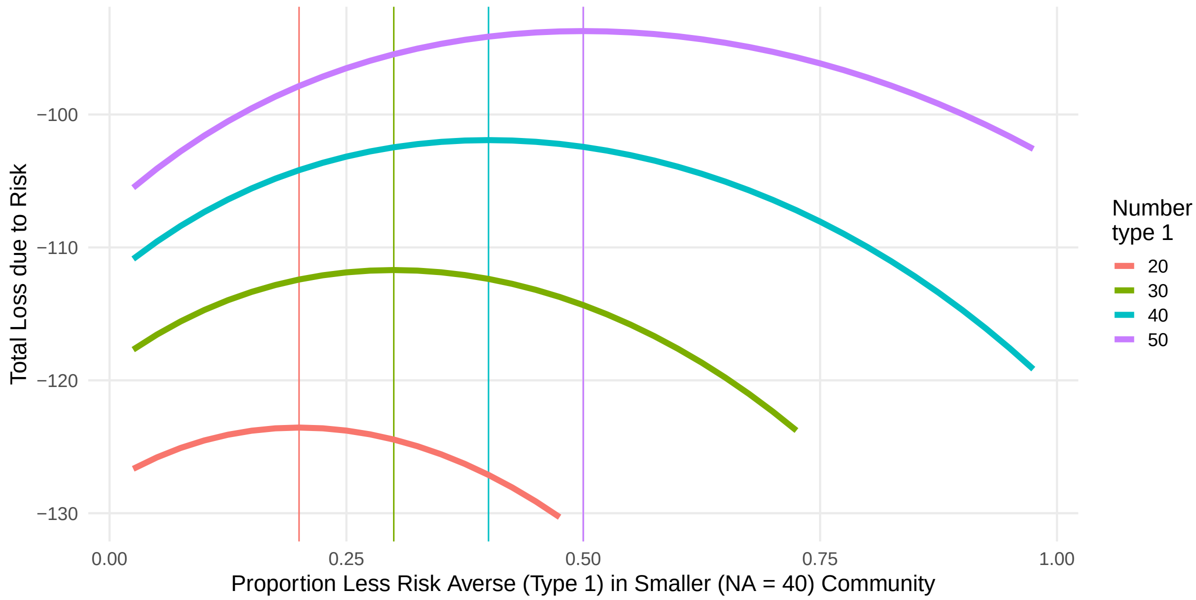


Figure 2: Optimal Allocation of Types Between Unequally Size Communities with varying numbers of Type 1 and Type 2 agents.

To simplify this problem, I consider the simple case where there is an equal number of more and less risk averse types. That is, $N_1 = N_2$. This implies that I can encompass the entire problem just by looking at one choice parameter, p_{1A}, and conditioning on the size of the smaller community, N_A. $p_{A1} = \frac{N_{1A}}{N_A}$, and I can express $p_{A2} = 1 - p_{A1}$, $p_{B1} = \frac{2N_{B1}}{N} = \frac{2(N_1 - N_{A1})}{N}$ and $p_{B2} = 1 - p_{B2}$. Setting $N_1 = N_2$ reduces the set of constraints to three, and simple computations take account of these three constraints. Hence, I have the problem

$$\begin{aligned} \max_{N_{A1}} \quad & N_{A1} V_1 \left(\frac{N_{A1}}{N_A} \right) + N_{A2} V_2 \left(\frac{N_{A1}}{N_A} \right) \\ & + N_{B1} V_1 \left(\frac{2(N_1 - N_{A1})}{N} \right) + N_{B1} V_2 \left(\frac{2(N_1 - N_{A1})}{N} \right). \end{aligned} \tag{14}$$

Solving this planners problem for an analytic solution is relatively difficult. However, it is easy to characterize the optimal allocation of types numerically. In Figure 1, I plot the objective in Problem 14 against p_{A1}, the new choice variable. To construct this example, I set $\sigma_c^2 = 100^2$, $N = 100$, $N_1 = N_2 = 50$, and set $\eta_1 \approx 0.0016$, $\eta_2 \approx 0.0037$, the means of these for the type 1 and type 2 in my data (see Section 4.3.1 for construction of coefficients of risk aversion and types).

Looking at Figure 1, welfare is maximized when $p_{A1} = 0.5$, when diversity of types is maximized. Likewise, welfare is minimized when as p_{A1} approaches 0 or 1, when diversity of types is minimized. Interestingly, unequal sized suboptimal communities improve over more equally sized suboptimal communities holding p_{A1} equal. Also interesting, welfare is not symmetrically suboptimal when the proportion of less risk averse agents strays from zero. If a community is overfilled with a type (i.e., $p_{A1} \neq 0.5$) it is better to "overfill" the smaller community with type 1 (less risk averse) agents as opposed to overfilling the larger community. For another way to look at this, in the appendix I plot the proportion of risk taken on by both groups in a risk pooling frontier (see Figure 17). Finally as a demonstration that this is not an artifact of equal sized communities, in 2, I vary the composition of types in the population. In this figure, welfare is maximized when $p_{A1} = p_1$, the proportion of type 1 agents in the population.

4 Data and Context

4.1 Data

The data comes from four villages in southern rural Ghana and features information about assets, income, consumption (positive and negative) shocks, and social networks (Barrett, 2009; Walker, 2011a). The survey instrument and further technical details can be found in Walker (2011b). After processing, the network data includes 631 individuals. The survey is of spouses in households, though I keep the data at the individual level. However, sample sizes for each empirical exercise vary, since the unit of analysis is not the individual. In the dyadic regressions, the sample size is the number of dyads, or the number of potential connections between individuals within villages. In the dyadic regressions, sample size = 71062. In the SUGMs, the sample size is determined by which feature is being estimated, and are reported in the estimation tables.

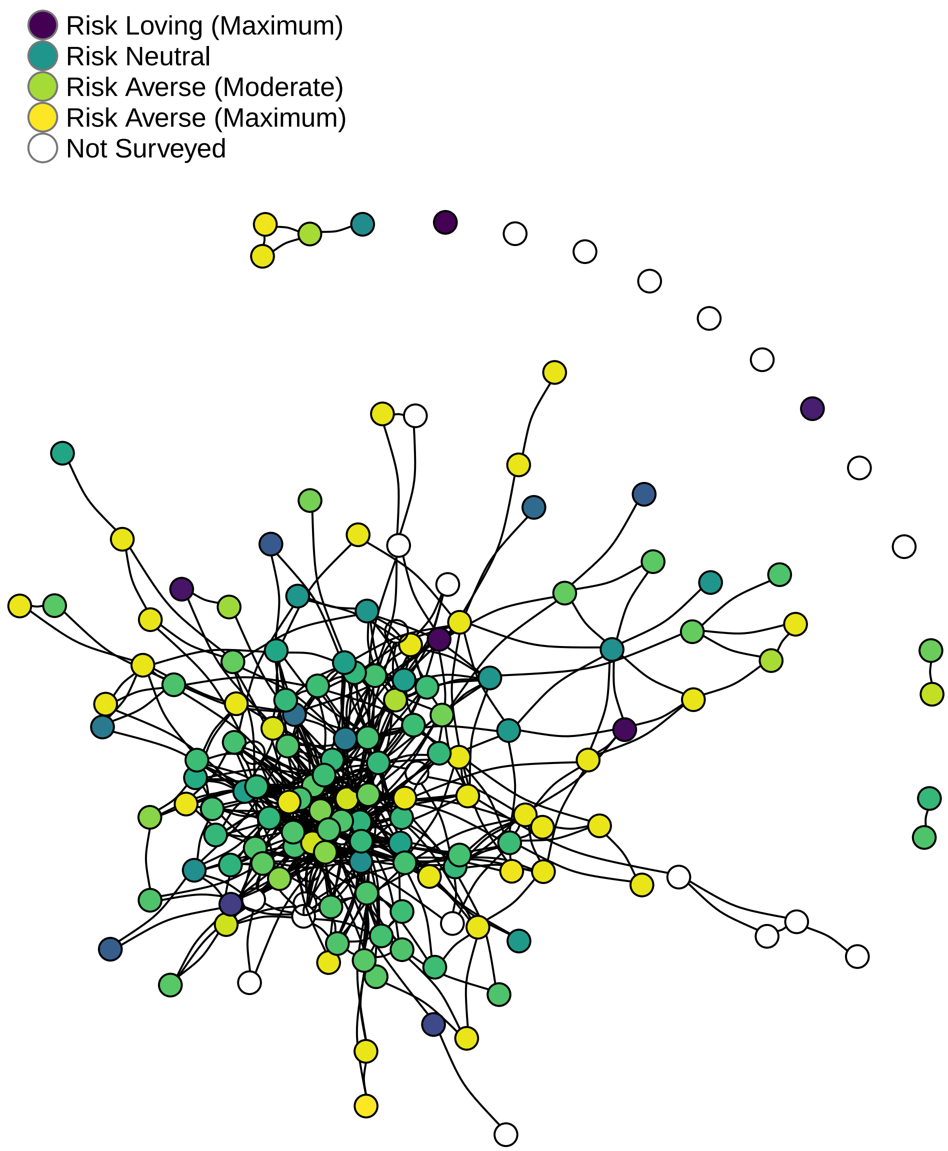


Figure 3: Risk Sharing Networks in Village of Darmang with Risk Aversion Indicated by Color

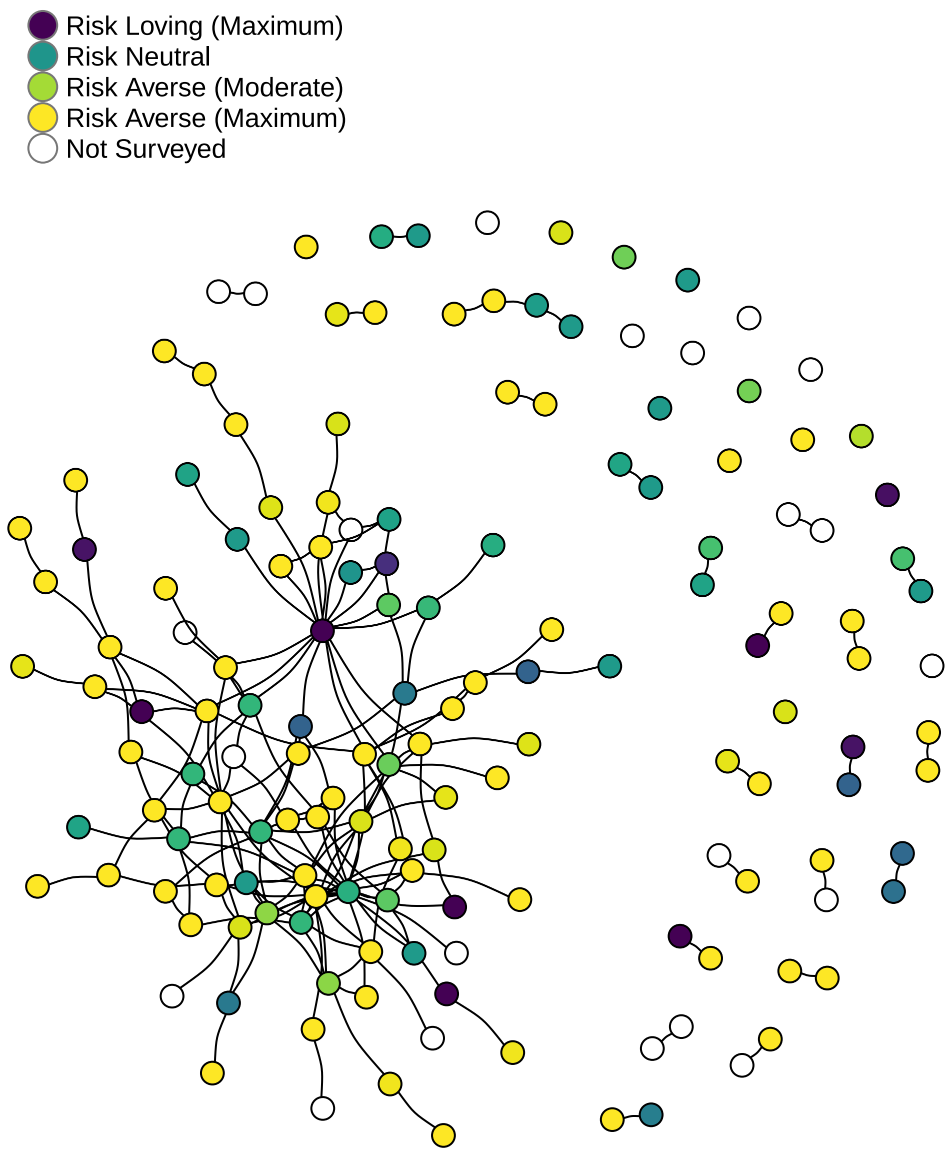


Figure 4: Risk Sharing Networks in Village of Pokrom with Risk Aversion Indicated by Color

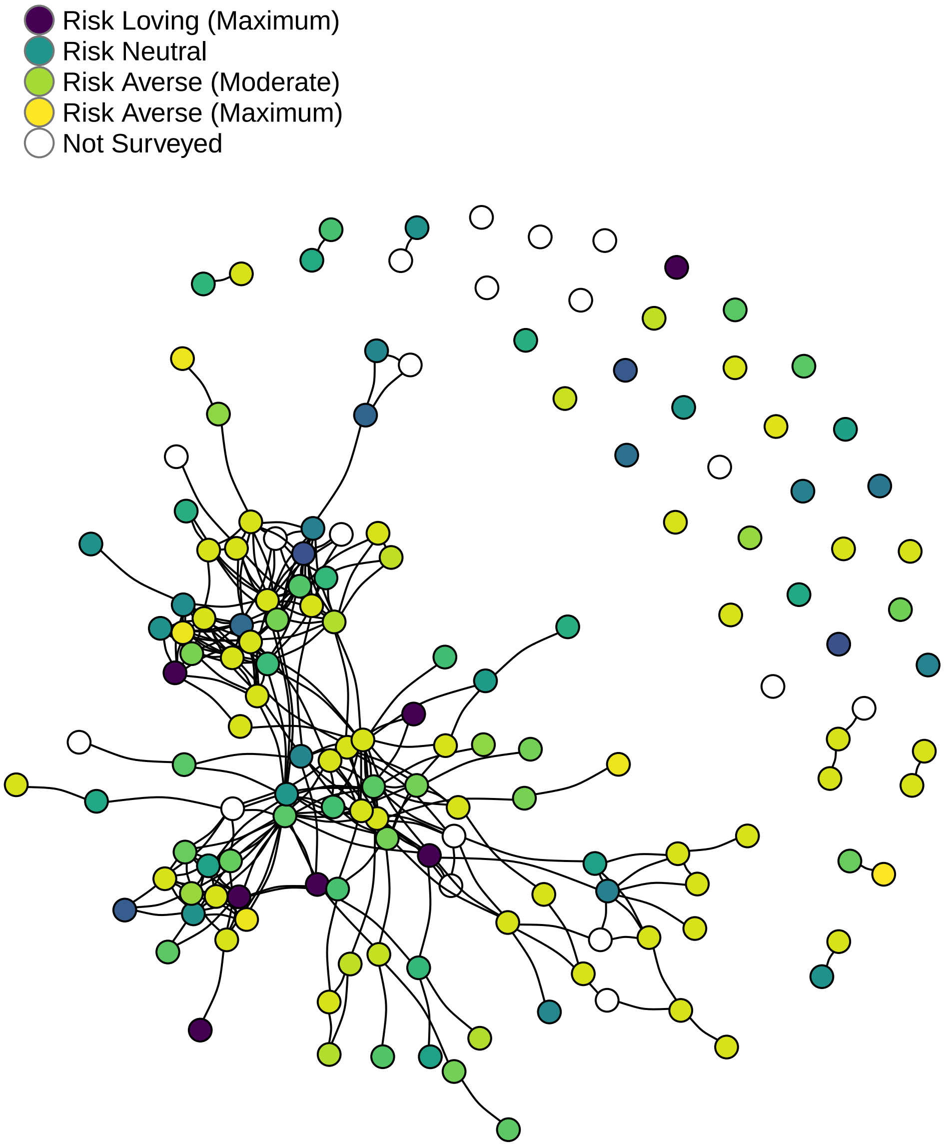


Figure 5: Risk Sharing Networks in Village of Oboadaka with Risk Aversion Indicated by Color

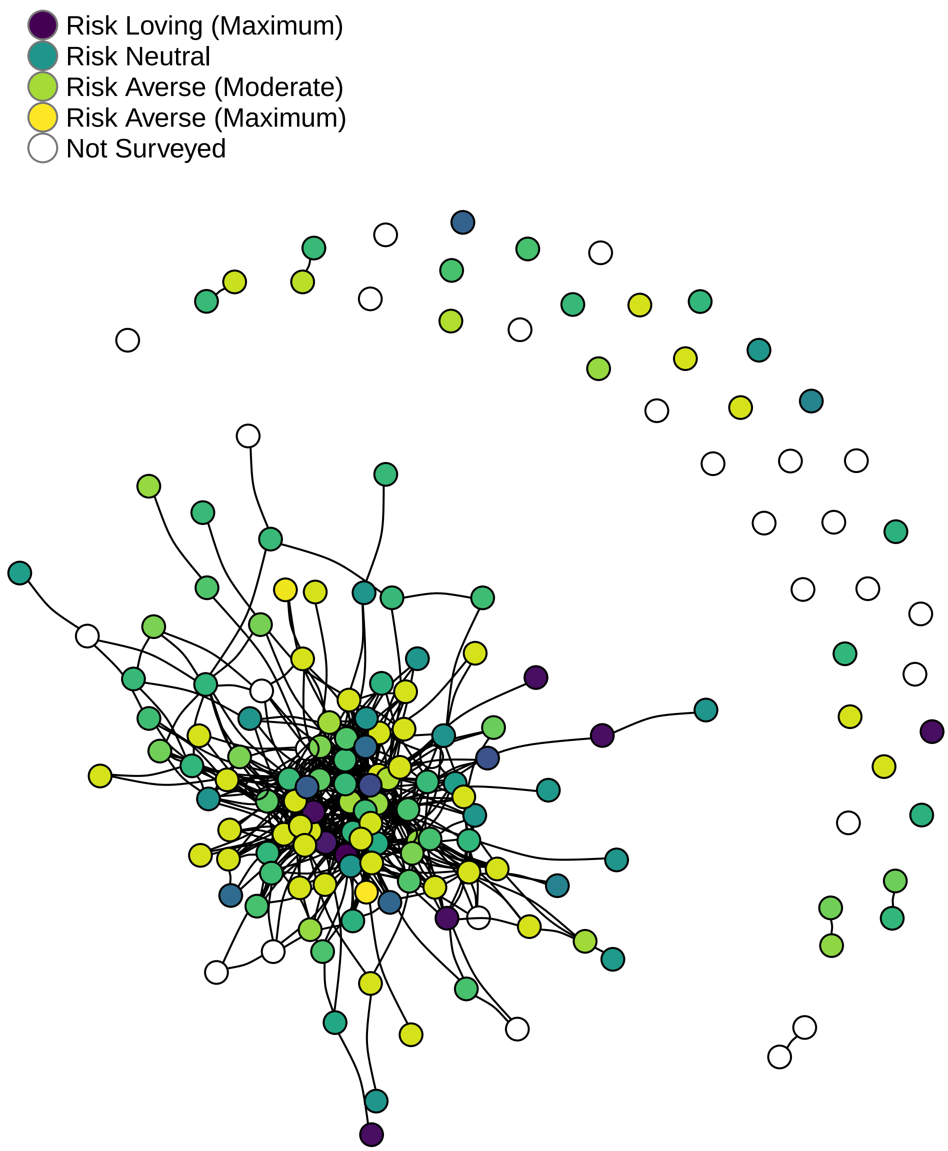


Figure 6: Risk Sharing Networks in Village of Konkonuru with Risk Aversion Indicated by Color

4.2 Risk and Coping in Ghana

The Pineapple export market, which is relevant to farmers in the data, can be a source of significant covariate risk (Conley and Udry, 2010). Suzuki et al. (2011) documents partial vertical integration in Pineapple markets, and explains this partial vertical integration as smallholders being better equipped to manage this risk.[2] Risk Coping in Ghana includes strong usage of informal networks. In the villages studied in the current work, these relationships are documented across decades (Udry and Conley, 2005; Walker, 2011a). These networks do not work equally well for all. In particular, for socially invisible members of the villages, risk pooling does worse that it does for their richer, more socially visible counterparts (Vanderpuye-Orgle and Barrett, 2009). Finally, as is often the case, the risk sharing relationships in this context suffer from various problems of asymmetric information. The networks are subject both to hidden income and limited commitment issues in general. Additionally, in the marital setting, spouses behave non-cooperatively, hiding income through gifts to their networks (Walker and Castilla, 2013; Nourani et al., 2019).

4.3 Variable Construction

To test hypotheses about assortative matching in risk sharing networks and do welfare simulations, I construct the data to match the theoretical model presented as closely as possible. In particular, I construct risk preferences assuming constant absolute risk aversion preferences and use community detection to construct risk pooling groups that serve as empirical analogues to the modeled risk pooling groups.

4.3.1 Risk Preferences

Leaving aside risk neutrality, using a set of four hypothetical gambles I use exponential preferences to measure individuals risk aversion. The first two menus presented are in the gains domain. In the first menu, the risky gamble Y_B is held fixed while increasing the sure

[2] This, in their estimation is due to secondary markets as opposed to risk sharing mechanisms.

payment Y_A. In the second, the sure payment is held fixed while reducing the upside of the gamble. The second set of gambles reflect the first set into a losses domain. For mathematical tractability, I assume Y_B is normally distributed. Combining this with the assumption of Constant Absolute Risk Aversion, I represent expected utility as a mean variance utility function (Sargent, 1987). I write

$$E(Y) - \frac{\eta_i}{2} V(Y)$$

Respondents are able to choose between two gambles Y_A and Y_B will be indifferent between the two when

$$E(Y_B) - \frac{\eta_i}{2} V(Y_B) = Y_A.$$

I assume that if an individual reaches a point of indifference between two gambles, I assign them to the midpoint between the two gambles. Hence, if the mean differs, I take the average of the mean of the two gambles and assign this value to the point of indifference. If the variance differs, I take the average of variances and assign this value to the point of indifference. The second two menus are reflections of the first two onto the domain of losses. Then we can express risk aversion for agent i as a function of their indifference point,

$$\eta_i = \frac{2(E(Y_B) - Y_A)}{V(Y_B)}$$

and recover the coefficient of absolute risk aversion. I compute $\hat{\eta}_i$ for each menu and individual. To combine these into measures of risk aversion, I average over menus.

4.3.2 Risk Sharing Network

To construct the risk sharing network, I use the intersection of a gift network and a trust network. To construct the gift network, a link occurs if individual i has received a gift from j and also if i has given a gift to j. In the trust network, I report a link if both i and j report trusting each other.[3] If a connection occurs in both networks, I record a connection

[3]Previously when this data has been used, this has been described as a strong ties network

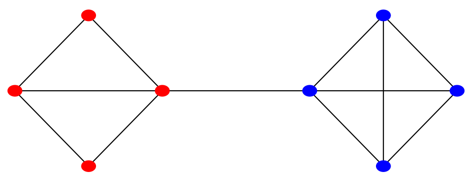


Figure 7: A Stylized Risk Sharing Network with (latent to the econometrican) communities denoted by red and blue.

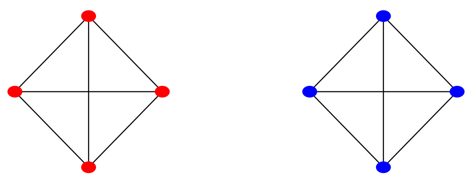


Figure 8: Community Network: After detecting the communities, community co-membership links are formed within the communities, but not across comunnities (even if they existed previously).

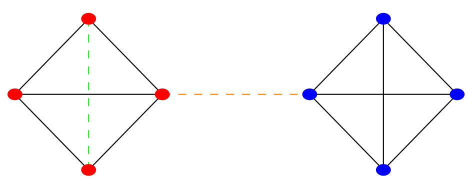


Figure 9: Difference in networks, community network less risk sharing network. Green is added, orange is removed. There is one additional connection within the red community and one less between the red and blue communities.

Table 1: Risk Sharing Network Summary Statistics by Risk Preferences

	More Risk Averse	Less Risk Averse	Risk Loving	Not Surveyed
Isolates	0.09	0.09	0.16	0.38
	(0.001)	(0.001)	(0.004)	(0.005)
Degree	4.62	6.61	4.79	2.72
	(0.02)	(0.03)	(0.06)	(0.05)
Clustering	0.25	0.23	0.23	0.17
	0.00	0.00	0.00	0.00
Betweenness	85.98	119.53	99.85	43.23
	(0.69)	(0.90)	(2.56)	(1.27)
Closeness	31.03	39.15	32.14	21.08
	(0.09)	(0.10)	(0.26)	(0.25)
N	236	217	96	82

Standard errors in parentheses.

between i and j and use this as my risk sharing network.

Table 1 presents risk sharing network summary statistics, aggregated across villages. Degree is a measure of centrality, which counts the number of individuals who are directly connected to an individual. Here I present the average degree. Isolates is computed as the proportion of individuals who are not connected to the network. Clustering is the average local clustering coefficient. This measures, for individual i connected to j and k, what proportion of the time are j and k also connected (also called transitivity). Betweenness and closeness are both measures of network centrality. Betweenness centrality measures how betweenness measures how central an individual is in a network by counting how many nodes it lies on the shortest path between. Closeness centrality measures the distance to the rest of the network. Individuals who are short distances on average from others in the network, will have high closeness centrality.[4] When comparing less and more risk averse individuals there are differences in almost every measure of centrality. Less risk averse individuals have lower degree, are closer on average to the rest of the network, and hold network position in

[4]In particular, I use harmonic closeness centrality, computed

$$C(i) = \sum_j \frac{1}{distance(i,j)}.$$

between more other individuals. Despite this, it's interesting to note that the difference in clustering between less and more risk averse individuals would appear to be economically small.[5]

5 Empirical Strategy

5.1 Community Detection

5.1.1 Intuition

To give intuition to the algorithm choice, consider a potential risk sharing process. A large gift is given to a randomly chosen individual in a risk sharing network. The household gives a gift to a (network) neighboring individual who is less well off than they are, sharing their positive shock equally. *Ex ante*, all the individual's neighbors should be equally likely to receive this gift.[6] Having received this gift, this individual is also is obligated to share with their worse off neighboring individual, provided they are not worse off than all of their network neighbors. This process of risk sharing continues. Eventually, the individual receiving the transfer ends with an effective shock which is still worse than their neighbors and gives no gifts. Progressively smaller transfers will "walk" randomly through the network. Individuals who are close to the individual who received the prize will have a high probability of receiving a transfer, while those far will have a low probability. Likewise, even if one does not receive a transfer in the first step, if an individual is connected to many of the same households as the one receiving the prize, they get additional chances for a gift. Within a dense and clustered portion of the network, most often the gains from the positive shock will

[5]Though it is not the topic of the current work, one might interpret this as a difference in linking social capital without an accompanying difference in bonding social capital. In terms of communities discussed later, this might also suggest that less risk averse individuals might be more likely to serve as liaisons between risk pooling communities, while being similarly integrated into the dense and clustered risk pooling communities as their more risk averse counterparts.

[6]There might be many reasons the household would feel obliged which might range from self-enforcing contracts, i.e., the threat of losing future access to their network (Coate and Ravallion, 1993; Ligon et al., 2002; Ambrus et al., 2014), or altruism (Bourlès et al., 2017).

not make it far, instead getting "trapped" in the local network.

Similarly, I can present this same intuition for negative shocks: a randomly chosen individual a negative shock. Based on a similar rule, they might request a favor from one of their neighbors, who might request a favor from one of their neighbors, and so on. Again, progressively smaller transfers walking through the network. Likewise, requests will remain trapped within dense and clustered portions of the network.[7]

5.1.2 Walktrap Algorithm

This process functions as a way risk is effectively pooled and mirrors the intuition of the *walktrap* algorithm. The walktrap algorithm uses random walks over the network to measure the similarity of nodes. The algorithm exploits the fact that a random walker in a graph tends to get "trapped" within tightly knit sections of the graph. A random walker starts at a random node i and moves to an adjacent node with probability $1/d(i)$ (where $d(i)$ is the degree of i). Then for each of a fixed number of periods, this process is repeated from the landing node, k, moving to an adjacent node with probability $1/d(k)$. If nodes are in the same community a random walk of fixed length from node i should often land on node j.

However, walks from node i frequently landing on node j is not a perfect condition for nodes to reside within the same community. First, nodes with high degree tend to receive more random walks, so far off individuals with high degree might be labeled as within the same community. For this reason, the measure of distance should take into account the degree of the receiving node. Second, individuals in the same community should see other nodes in the the network similarly. Pons and Latapy (2004) uses this second fact to build a measure of similarity.

$$r_{ij} = \sqrt{\frac{\sum_{k=1}^{n}(P_{ik}^{s} - P_{jk}^{s})^2}{d(k)}}$$

[7]The validity of this process isn't essential for the success of the algorithm of course. Many parallel reasons might point the same direction. For example, tightly knit networks might serve as more useful to overcome information asymmetries in networks if information is passed along the same links (Bloch et al., 2008).

where P_{ik}^{s} is the probability of a random walk of length s from node i landing on node k. The algorithm works by iteratively merging nodes who are similar into communities.

The algorithm starts by assigning each node into its own community in the network. Similarities are computed between adjacent nodes using the measure above and the closest two communities are merged. Then, the merged community remains in the network as a single node (with all its out of community links preserved). Similarities are updated and the process repeats until all nodes are merged into one community. This builds a *dendrogram*, or a tree depicting the merges of nodes into communities. Each merge is depicted by a split in the tree. This gives us many possible community assignments. To choose an optimal community assignment, a tuning statistic called *modularity* is used to cut the dendrogram at one of the splits.

Modularity measures the internal quality of the community by looking at how many links exist within the community compared to a how many would be expected at random. The measure follows from a thought experiment: suppose you were to take a graph and randomly "rewire" it. This rewiring preserves the degree of individual nodes, while destroying the community structure. The average number of within community links from rewiring is used as a counterfactual. Having many more links within the community than the counterfactual implies a good community detection, fewer implies a poor community structure. For more about modularity, including the formal definition, please see Appendix D.1.3.

5.1.3 Networks Arising From Community Detection

After I have assigned nodes to communities, I construct an additional risk sharing network using these community assignments. Assuming that effective risk pooling takes place at the community level, all nodes assigned to a given community are linked within the network. Additionally, I assume no risk sharing takes place between communities and so in this network, no links occur between communities. I represent the community graph using an adjacency matrix C where $c_{ij} = 1$ if i and j are in the same community and 0 if not. Like the adjacency matrix, C is symmetric. I use this network in dyadic regression and SUGMs to measure who you pool risk with in effective terms. The differences in the bilateral risk sharing network and the community networks are depicted in Figures 7, 8, and 9.

5.2 Dyadic Regression

Before diving into the SUGMs, it is useful to estimate dyadic regressions. While dyadic regressions cannot handle "higher order" features like stars or triangles, they are familiar, interpretable as regressions, and comparable with past literature. In particular, I note similarities and differences between these results and those found in Attanasio et al. (2012).

5.2.1 Naïve Specification

In these regressions, each pair of nodes is treated as an observation. Let $a_{ij} = 1$ if individual i has given and received gifts from j and both i and j trust each other. Hence our dependent variable is the risk sharing network defined by using trusted gift givers. This construction requires that $a_{ij} = a_{ji}$ so the adjacency matrix A is symmetric. In addition, as required by Fafchamps and Gubert (2007) all explanatory variables also enter symmetrically. In particular, I estimate a set of four linear probability models. The most parsimonious model regresses risk sharing connections on differences in measured risk aversion,

$$a_{ij} = \beta_0 + \beta_1 |\eta_i - \eta_j| + \varepsilon_{ij} \tag{15}$$

where η_i is the risk aversion of individual i and ε_{ij} is the error term. Here (as in the following specifications) a negative estimate β_1 is evidence of assortative matching, i.e., that individuals prefer to share risk with individuals who have similar risk preferences to their own. To interpret these regressions as measuring preference for assortative matching on risk preferences, the goal becomes addressing omitted variable bias originating from two key sources: popularity and homophily.

5.2.2 Omitted Variables: Addressing Popularity and Homophily

There are three basic stories about what might cause risk preferences to be correlated with popularity. First, risk preferences could be correlated with unobservable personality traits. For example, it could be that less risk averse agents differ in personality traits not directly related to risk preferences. Second, economic decision making specifically involving risk might alter someone's fortunes and thus their social standing. In particular, I would expect lower risk aversion individuals to make riskier, higher reward decisions. Moreover, their increased wealth and income would only make them more useful for the purpose of risk pooling, and hence they would be desirable to make connection to. Third, though I have assumed constant absolute risk aversion, it is plausible that having better social standing could make a person less risk averse. A fourth issue is also at play: even when risk aversion is not correlated with popularity, as outlined in Graham (2017), a person well connected to all types might be measured as not harboring a preference for similar risk-preferenced others when in fact they do.

From the intuition here, in a dyadic regression, I would seek to control for this popularity one of two ways. First, I can used a fixed effects approach to estimate degree heterogeneity.[8] Ideally, Graham (2017) lays out such an approach for estimating models of network formation with degree heterogeneity called Tetrad Logit (TL), itself an extension of dyadic regression. Unfortunately, at the moment the TL estimator is only implemented for single network estimation.[9] A second best solution is to control for observable aspects that might determine popularity in the risk sharing network. These might include social network centrality, economic and demographic variables, and based on the story above about economic decision-making, risk aversion. I take the story of risk aversion as paramount in this context, especially given that preferences (even risk preferences themselves) often fluctuate

[8] I cannot control for degree heterogeneity directly because this is a form of "bad control," though this is probably subtle.

[9] Single network *asymptotics* are a feature of the TL estimator, but it is difficult to summarize the results of four regressions. Regardless, I intend to include TL estimates in the near future.

across contexts. More to the point, I have a concrete story of exactly why risk aversion matters for network formation outside of assortative matching.[10] Where one or both have low risk aversion, I would expect these agents to be more popular and hence have a higher probability of forming a link.[11]

On the other hand, it could be that assortative matching on risk preferences could be assortative matching on some other social or economic dimension. In addition to inclusion of kinship and risk aversion, my approach for controlling for other observables related to popularity and homophily will be straightforward. Homophily is a common feature of social networks and is similarly present in the context of risk pooling (de Weerdt, 2002; Fafchamps and Gubert, 2007; Jaramillo et al., 2015). I measure economic factors using occupation and social similarity using gender, age, and schooling. In additional specifications I will control for specific pre-existing family relationships, controlling for if a dyad is married or is made up of co-wives. Finally, all specification will feature village fixed effects.

5.2.3 Further Specifications and Interpretation

A second specification includes the sum of risk aversion η_i and η_j to control for the correlation between risk aversion and degree.

$$a_{ij} = \beta_0 + \beta_1|\eta_i - \eta_j| + \beta_2(\eta_i + \eta_j) + \varepsilon_{ij} \tag{16}$$

A positive estimate of β_2 suggests that individuals who are more risk averse are less likely to link to each other. A third specification examines kin ties as a predictor of risk sharing connections.

$$a_{ij} = \beta_0 + \beta_1|\eta_i - \eta_j| + \beta_3 f_{ij} + \varepsilon_{ij} \tag{17}$$

[10] This argument is not to neglect other factors, which certainly matter, but to set priorities.

[11] Why is the sum of risk aversion not a bad control? It was fixed at the same time as the regressor of interest, since it's just a different computation of this regressor of interest.

where family is $f_{ij} = 1$ when i and j report being family members. A positive estimate of β_3 suggest that family are more likely to be connected within the risk sharing network. A fourth specification combines specifications 15 and 16.

$$a_{ij} = \beta_0 + \beta_1|\eta_i - \eta_j| + \beta_2(\eta_i + \eta_j) + \beta_3 f_{ij} + \varepsilon_{ij} \tag{18}$$

Finally, a fifth specification introduces interactions between the difference in coefficients of risk aversion and family ties.

$$\begin{aligned} a_{ij} = \beta_0 + &\beta_1|\eta_i - \eta_j| + \beta_2(\eta_i + \eta_j) + \beta_3 f_{ij} \\ &+ \beta_4 f_{ij} \times |\eta_i - \eta_j| + \varepsilon_{ij} \end{aligned} \tag{19}$$

A negative estimate of β_4 is evidence that assortative matching is stronger among family members. Moreover, if $\beta_1+\beta_4$ is negative, this provides evidence that within family members, risk aversion is an important determinant of risk sharing connections.

5.2.4 Community Network

I re-estimate regressions 15, 16, 17, 18, and 19 with detected communities as the network (as opposed to the network adjacency matrix). In all of the above specifications, I replace a_{ij} with c_{ij}, the ijth entry of the community matrix C. $c_{ij} = 1$ if i and j are in the same detected community, and 0 otherwise. Degree sum is included in the re-estimation of 16, 18 and 19. Importantly, as I consider the community network in dyadic regression, I still view it as possible that a given agent could join any community in a village and have access to their network, hence set of dyads under consideration does not change from the risk sharing network models.

5.2.5 Estimation and Standard Errors

As mentioned above, I estimate these regressions as linear probability models, though results are similar estimating logistic regressions (see Tables 11 and 12 in Appendix A). Note however, that the errors are non-independent. In particular, the residuals of dyads involving a particular node might be arbitrarily correlated, i.e., $Cov(\varepsilon_{ij}, \varepsilon_{lk}) \neq 0$ if $i = l$, $i = k$, $j = l$, or $j = k$. To correct standard errors for this non-independence, I use dyadic robust standard errors as proposed by Fafchamps and Gubert (2007) and discussed in Cameron and Miller (2014). The asymptotic properties of this estimator are described in Tabord-Meehan (2019).[12]

5.3 Subgraph Generation Models

5.3.1 Intuition

A useful tool for understanding risk sharing networks and communities is called a Subgraph Generation Model (SUGM). SUGMs treat networks as emergent properties of their constituent subgraphs.[13] A *subgraph* (or induced subgraph) of a graph is the graph obtained from taking a subset of nodes in the graph and all edges connecting those nodes to each other. For example, for a subset of two nodes in a graph, the subgraph will be either a link or two unconnected nodes. For three nodes, the subgraph might be a triangle (a trio of nodes all connected by edges), a line (one node connected to the two others), a pair and an isolate (only two nodes connected), or an empty subgraph (three unconnected nodes). In general, I focus on connected subgraphs for the SUGM. In three node example above, the means I leave aside the pair and isolate and the empty subgraph, focusing on the triangle and the

[12]When a natural unit of clustering is present, as in Attanasio et al. (2012), that can be used to cluster standard errors as opposed to dyadic robust. Unfortunately, in our case, the data does not feature such a unit.

[13]While Exponential Random Graph Models have similar motivation, they do not succeed at reconstructing graphs with any success. They depend on an assumption of independence of links, if this does not hold they are not consistent. To the contrary, much of the theory of risk sharing would expect links are dependent on each other (Chandrasekhar and Jackson, 2018).

line. Likewise, while a link is an interesting subgraph, two unconnected nodes is not. When describing these models, I will use "features" of the SUGM interchangeably with subgraph.

While SUGMs can be estimated using GMM, I am able to directly estimate the parameters using an algorithm given by Chandrasekhar and Lewis (2016) and Chandrasekhar and Jackson (2018). Estimating a SUGM directly is essentially estimating the relative frequency of various subgraphs in a network. However, I can't stop at simply estimating the features. Because networks are the union of many subgraphs, subgraphs might overlap and incidentally generate new subgraphs. For example, three links placed between ij, jk, and ik would incidentally generate a triangle. I want to estimate the true rate of subgraph generation. To do this, I order subgraphs by number of links involved in their construction. Then, I compute the number of subgraphs generated of that type, but only if they are not a portion of a "larger" subgraph. For subgraphs of same size, order is arbitrary, but must exclude occurrences of this subgraph incidentally generated by other subgraphs who are further along in the order. For example, for a SUGM featuring links and triangles, I order links first, triangles second, etc. While counting links and potential links, I neglect pairs of nodes ij if jk and ik are in the graph.[14] This algorithm yields consistent estimates of the true rate that these subgraphs are generated at.

5.3.2 Links and Isolates Subgraph Generation Model with Types

I start by estimating three simple SUGMs on the risk sharing network, using only links and isolates as features. The SUGMs seek to understand how individuals of different risk preferences connect to each other. For various reasons, a small subset of individuals in the network did not participate in the survey module that recovered risk preferences.[15] Hence, I start with a 2-type model to diagnose the differences between those individuals who

[14] If I to add lines of three nodes, I could order these before or after triangles. Ordering lines before triangles I would look at potential links ij and jk where ik is not in the graph. Likewise, I would need to remove pairs of nodes ij if jk or ik are in the graph.

[15] Some of these individuals were not surveyed at all, but appear in the network, others may be part of the sample who missed that particular round or module.

participated and those who did not. I estimate five features: Isolates of surveyed nodes, isolates of nodes who were not surveyed, and links within surveyed nodes, links between surveyed nodes and non-surveyed nodes.

Of those in the network who have a risk aversion coefficient, I split these individuals into three groups: risk loving, less risk averse, and more risk averse. Risk loving are those with $\eta < 0$. This accounts for about 20% of the individuals with preferences. I split the remaining risk averse individuals into evenly sized groups of 40% each, with more risk averse individuals being above a cut-point. The second model estimates the full model with risk averse, risk loving and non-surveyed types for a total of three types. Third, I estimate the full model splitting risk averse individuals into more and less risk averse types.

For each model I estimate $\tilde{\beta} = \left(\{\tilde{\beta}_{I,\ell}\}_{\forall \ell}, \{\tilde{\beta}_{L,\ell,\ell}\}_{\forall \ell}, \{\tilde{\beta}_{L,\ell,r}\}_{\forall \ell, \forall r}\right)$. Coefficients for isolates of type l, $\tilde{\beta}_{I,\ell}$ are estimated

$$\tilde{\beta}_{I,\ell} = \frac{\sum_{i=1}^{n} \mathbf{1}(deg(i) = 0 | l_i = \ell)}{n_\ell}, \tag{20}$$

coefficients for within links of type ℓ, $\tilde{\beta}_{L,\ell,\ell}$ are estimated

$$\tilde{\beta}_{L,\ell,\ell} = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \times \mathbf{1}(l_i = \ell) \times \mathbf{1}(l_j = \ell)}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{1}(l_i = \ell) \times \mathbf{1}(l_j = \ell)}, \tag{21}$$

and coefficients for links between type ℓ and type r, $\tilde{\beta}_{L,l,r}$ are estimated

$$\tilde{\beta}_{L,l,r} = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \times (\mathbf{1}(\ell_i = l) \times \mathbf{1}(\ell_j = r) + \mathbf{1}(\ell_i = t) \times \mathbf{1}(\ell_j = l))}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{1}(\ell_i = l) \times \mathbf{1}(\ell_j = r) + \mathbf{1}(\ell_i = t) \times \mathbf{1}(\ell_j = l)}. \tag{22}$$

From proposition C.2 in Chandrasekhar and Jackson (2018) under some sparsity conditions[16], $\Sigma^{-1/2}(\tilde{\beta}_n - \beta_0^n) \to N(0, I)$ where β_0^n is the true rate of subgraph generation. For a feature ℓ,

[16] A first note here is that these networks are sparse by the definition of Chandrasekhar and Jackson (2018). If I assume a constant growth rate of the density of links, then density is growing at about $n^{1/3}$ or less (which is acceptable). For this particular model, none of the features chosen can incidentally generate any other feature. For example, links cannot generate isolates, nor can isolates generate links. Because the second is true, for this particular model the conditions from Chandrasekhar may be cracking a walnut with a sledgehammer, so to speak.

the variance of the feature is the entry on the diagonal:

$$\Sigma_{s,s} = \frac{\beta^n_{0,s}(1 - \beta^n_{0,s})}{\kappa_s \binom{n}{m_s}} \tag{23}$$

where m_s is the number of nodes involved in the feature and κ_s is number of different possible relabelings of the feature (note: for both isolates and links $\kappa_s = 1$). So I estimate the standard errors of the SUGM,

$$\tilde{\sigma}_{s,s} = \sqrt{\frac{\tilde{\beta}^n_s(1 - \tilde{\beta}^n_s)}{\kappa_s \binom{n}{m_s}}}. \tag{24}$$

For the results, $\kappa_s \binom{n}{m_s}$ is the "sample size" of the feature.

5.3.3 Pooled Subgraph Generation Models

Since network data I am using has four networks, I need to make choices as to how to handle these multiple networks in the Subgraph Generation Model. One approach would be to estimate a subgraph generation model for each village and average the coefficients of these. A different strategy, and one that relies on the same asymptotics as the single network case from Chandrasekhar and Jackson (2018) is to pool the counts and potential counts from the villages to estimate a single coefficient across the villages. This leads to an adjusted class of SUGMs I term Pooled SUGMs. I decide on these for the ability to lean on the same asymptotic theory as the single network case. However, a few considerations need to be made. Principally, I can't simply combine the networks and run the SUGM. For example, it is unlikely that the dyads that would occur between villages would be reasonable potential dyads. Hence I need to collect counts of features and potential counts of features in all four villages before combining. Let $count_{sv}$ be the count of some subgraph s in village v and $potential_{sv}$ be the potential number of times that feature could occur. These reflect the numerator and denominator, respectively, of equations 20, 21, and 22 above. I estimate the coefficient associated with some subgraph s

$$\tilde{\beta}_s = \frac{\sum_{v=1}^{4} count_{sv}}{\sum_{v=1}^{4} potential_{sv}} \tag{25}$$

This uses only the relevant potential occurrences of the feature. Similarly, when estimating the standard errors of a feature, I cannot use the same effective sample size as I would use if I combined the networks. Let n_v be the number of nodes in the village network. If I take $\kappa_s\binom{\sum n_v}{m_s}$ I would include many combinations of nodes that in reality could not form the subgraph in question. Hence I estimate the standard errors the of pooled SUGM

$$\tilde{\sigma}_{s,s} = \sqrt{\frac{\tilde{\beta}_s(1-\tilde{\beta}_s)}{\kappa_s \times \sum_{v=1}^{4}\binom{n_v}{m_s}}}. \tag{26}$$

5.3.4 Differences in Assortative Matching

These SUGM estimates give me a way to test for assortative matching between preferred and effective risk sharing networks. However, since the the risk sharing network and the community network have different degrees of attachment, to make an apples to apples comparison, I normalize my results by taking a ratio of coefficients. In particular, I compare the estimates of the 4-type SUGM with the results of the 3-type SUGM focusing on three coefficients of interest. These are within links for type 1 agents, within links for type 2 agents, and links between type 1 and two agents. For all three, I compare these links to the coefficient on links within any risk averse agents. Doing this for both the community coefficients and the bilateral network coefficients, I can compare which correspond to within links for agents of type 1, within links for agents of type 2 and links between types. For the current results, I construct approximations for the mean and variance of these ratios using approximations for the mean and variance of a ratio[17], and using parameter estimates as stand-ins for their means, I can use an analytic expression for the variance. See appendix D.2 for more.

[17]https://www.stat.cmu.edu/ hseltman/files/ratio.pdf

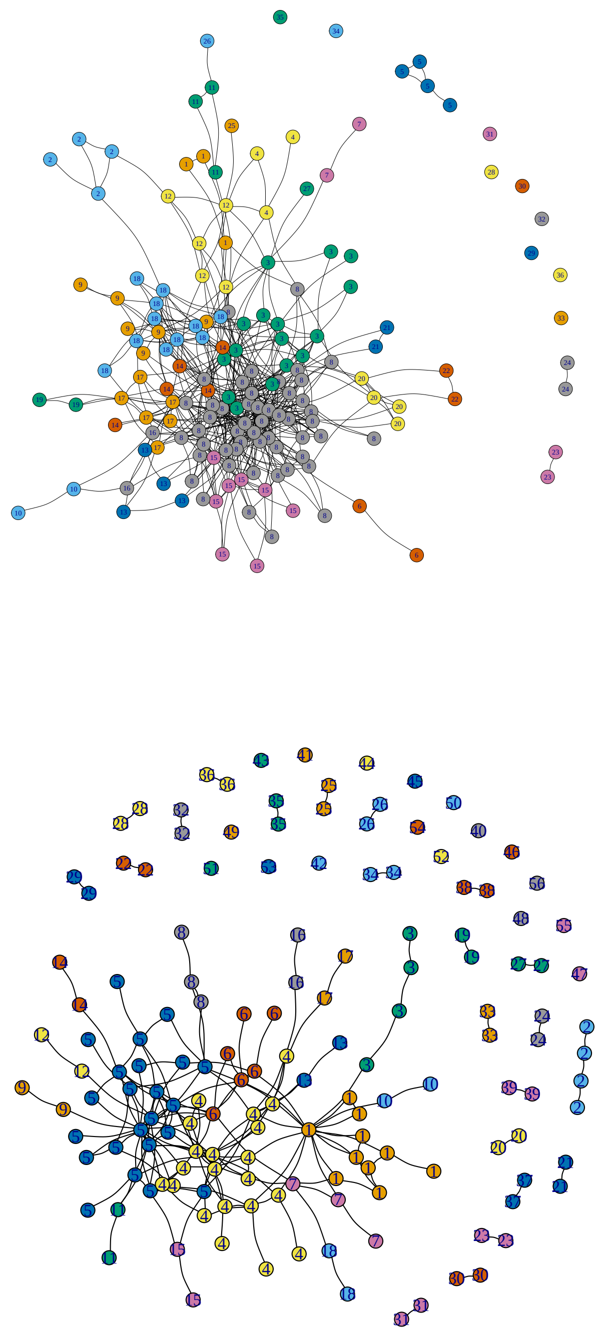
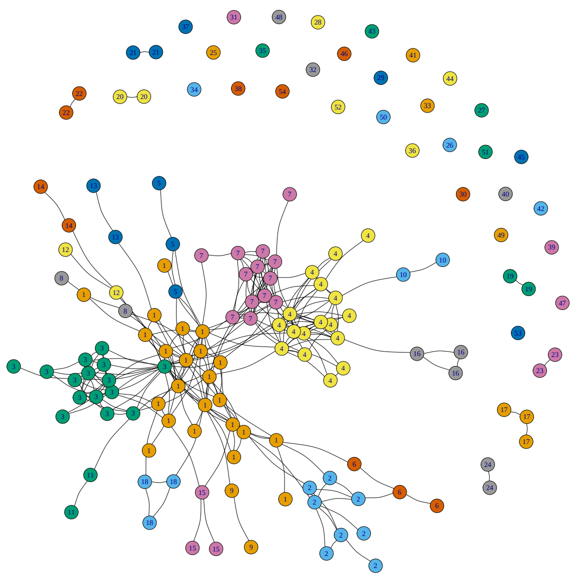


Figure 10: Risk Sharing Networks in Darmang (top) and Pokrom (bottom) with walktrap community detection (colors and numbers represent communities).



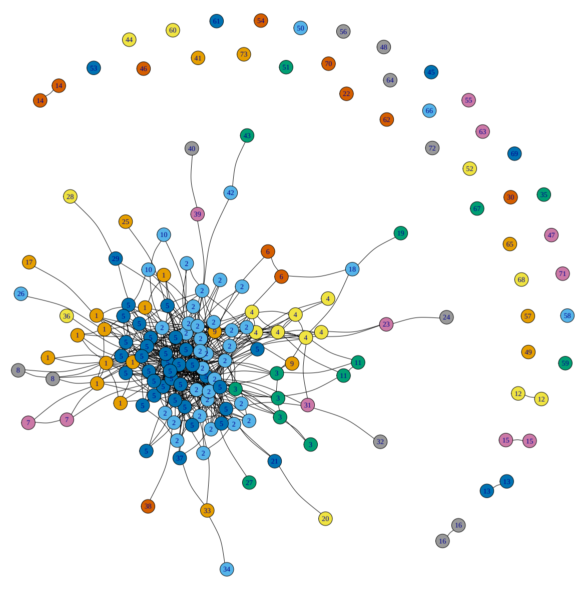


Figure 11: Risk Sharing Networks in Oboadaka (top) and Konkonuru (bottom) with walktrap community detection (colors amd numbers represent communities).

6 Results

6.1 Community Detection

I assign individuals to risk pooling communities using walktrap community detection with walks of four steps applied to our risk sharing network. I general, longer walks tend to result larger communities, whereas smaller walks result in smaller communities.[18] For the resulting community detection see Figures 10 and 11.

6.2 Dyadic Regression

6.2.1 Risk Sharing Network

Table 2 reports the results from estimating equations 15, 16, 17, 18, and 19. I include village level fixed effects in all dyad regression specifications, though this does not effect the magnitudes estimated in any of the specifications. Reported t-statistics have been adjusted by clustering at the dyad level. To make results more interpretable, I transform risk aversions into z-scores before computing regressors. This changes the interpretation just a bit. For example, β_1 estimates the effect of a one-standard deviation absolute difference in risk aversion.

Column 2 and 5 present my preferred specifications. Across all specifications I see negative estimates of β_1 or $\beta_1 + \beta_4$. However, in columns 1 and 3, when the sum of risk aversion is omitted from the model, the estimates are small in magnitude and are not statistically significant (at any standard confidence level). In contrast, controlling for degree in column 2 yields a negative and significant (at the 1% level). I estimate a one standard deviation difference in risk aversion leads a 2.16 percentage point reduction in the probability of linkage.

Family connections are also a strong determinant of linkage in the risk sharing network. Across specifications 3, 4, 5, having a family connection is positively associated with linkage in the risk sharing network (statistically significant at the 0.1% level). In column 5, family

[18] As is the case in this data.

Table 2: Dyadic Regression: Bilateral Risk Sharing Network

	(1)	(2)	(3)	(4)	(5)
$\lvert\eta_i - \eta_j\rvert$	-0.00991	-0.0216**	-0.00239	-0.0187**	-0.0154*
	(-1.11)	(-2.79)	(-0.32)	(-2.95)	(-2.28)
$\eta_i + \eta_j$		-0.0133		-0.0185**	-0.0185**
		(-1.84)		(-3.09)	(-3.10)
family_{ij}			0.517***	0.518***	0.537***
			(32.22)	(32.43)	(29.21)
$\text{family}_{ij} \times \lvert\eta_i - \eta_j\rvert$					-0.0197*
					(-2.06)
Village FE	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	No
N dyads	71052	71052	71052	71052	71052
R^2	0.0180	0.0193	0.2346	0.2371	0.2374

t statistics in parentheses

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

member dyads are 53.7 percentage points more likely to form a risk sharing relationship as non-family members.

In columns 4 and 5, when I control for family connection and risk aversion, the estimate of β_1 is once again insignificant (and positive in column 5). However, this may speak more to the mechanism of assortative matching. Similar to Attanasio et al. (2012), I would expect assortative matching on risk aversion to play a stronger role for more socially proximate individuals, who have more information about each others preferences. In column 5, I have $\beta_1 + \beta_4 = -0.0351$, statistically significant at the 0.1% level ($\chi^2(1) = 13.68$). Interpreting the coefficient, between family members a one standard deviation difference in risk aversion reduces the probability of linkage by 3.51 percentage points.

6.2.2 Community Network

Table 3 reports the results from re-estimating equations 15, 16, 17, 18, and 19 with the community network as the outcome. The estimates of β_1 are negative and small in magni-

Table 3: Dyadic Regression: Community Network

	(1)	(2)	(3)	(4)	(5)
$\lvert\eta_i - \eta_j\rvert$	-0.00668	-0.00651	-0.00343	-0.00525	-0.00379
	(-1.38)	(-1.20)	(-0.79)	(-1.05)	(-0.75)
$\eta_i + \eta_j$		0.000189		-0.00207	-0.00206
		(0.04)		(-0.53)	(-0.53)
family_{ij}			0.224***	0.224***	0.232***
			(13.56)	(13.55)	(11.71)
$\text{family}_{ij} \times \lvert\eta_i - \eta_j\rvert$					-0.00882
					(-0.84)
Village FE	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	No
N dyads	71052	71052	71052	71052	71052
R^2	0.0125	0.0125	0.0997	0.0998	0.0999

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

tude. None are statistically significantly different than 0 at any standard significance levels. Likewise, in column 5, $\beta_1 + \beta_2 = -0.012$ is not significantly different than zero at standard significance levels ($\chi^2(1) = 1.36$). Hence, I fail provide evidence for assortative matching in the community network regressions.

6.2.3 Robustness

Qualitatively, the results in 2 and 3 are highly robust to controlling for demographic factors and network centrality, both overall and column by column. See Tables 9 and 10 in Appendix A for results with baseline control variables added[19] In general, the magnitude of β_1 falls when controls are included. For example, in Column 2, the estimate of β_1 falls to -0.107 (still statistically significant at the 5% level). One other important difference is that β_1 and β_4 no longer enter significantly individually in Column 5, suggesting that family may

[19] In particular, I control for if the pair is married, are co-wives, have the same occupation, are the same gender, have the same level of schooling, are both men, are both primary, secondary, or tertiary educated (no/missing education left out), and for sums and absolute differences in: age, (family network) degree centrality, betweenness centrality, and eigenvector centrality.

be proxying for other social factors now controlled for. However, $\beta_1 + \beta_4 = -0.018$ remains statistically significant from zero in this specification but now at the 5% level ($\chi^2(1) = 4.85$).

6.3 Subgraph Generation Models with Types

6.3.1 Risk Sharing Network

The main SUGM results are presented in tables 4 and 5. While these are abridged for clarity, full results of all SUGM models are available in Appendix A. Using this model, I estimate that individuals who are risk averse tend to form links to each other at a rate of 4.04%. The network arising from community detection tends to be denser than the risk sharing network: I estimate that individuals who are surveyed about preferences tend to form links to each other at a rate of 9.28%, more than twice the rate in the risk sharing network.

Model, Subgraph	Coef.	Std. Err.
Baseline SUGM		
Within: Risk Averse	0.0404	0.0009
Preferences SUGM		
Within: Less risk averse	0.0561	0.0010
Within: More risk averse	0.0299	0.0008
Between: More, less risk averse	0.0360	0.0008

Table 4: Links and Isolates Pooled Subgraph Generation Model: Risk Sharing Network. Abridged models, sample size = 49536 dyads.

Moving past the baseline model to the main model I derive two main findings. First, I see further evidence of assortative matching on risk preference by less risk averse individuals. Less risk averse agents form within-type links at a rate of 5.61% (compared to the base rate of 4.04%). Second, I do not see the same kind of assortative matching when looking at more risk individuals: I estimate more risk averse individuals form within-type links at a rate of 2.99%, lower than both the base rate and the rate at which less and more risk averse individuals form links between type (3.60%). In this way, low risk aversion individuals drive

Model, Subgraph	Coef.	Std. Err.
Baseline SUGM		
Within: Surveyed	0.0928	0.0013
Preferences SUGM		
Within: Less risk averse	0.1189	0.0015
Within: More risk averse	0.0713	0.0012
Between: More, less risk averse	0.0876	0.0013

Table 5: Links and Isolates Pooled Subgraph Generation Model: Community Network. Abridged models, sample size = 49536 dyads.

assortative matching. In contrast, more risk averse types are more likely to form between links than within links.

6.3.2 Community Network

The assortative matching in the community network mirrors the pattern the risk sharing network. First, it is driven by less risk averse individuals, who form within links at a rate of 11.89%. Second, links between low and high risk aversion individuals form at a higher rate (8.76%) than links within high risk individuals (7.13%).

However, when making an apples to apples comparison between the degree of assortative matching in the risk sharing network and the degree in the community network, I see that the degree of assortative matching falls in the community network. Measuring the degree of assorative matching as the ratio of the rate of between links to the rate of links between all risk averse individuals, see Tables 6 and 7. The ratio of within for less risk averse is higher in the risk sharing network, whereas the ratio of between is lower. Essentially, this indicates a reduced degree of assorative matching in the effective risk sharing communities.

Model(s), Subgraph	Ratio	Std. Err.
Preferences/Baseline		
Within: Less risk averse	1.389	0.0336
Within: More risk averse	0.740	0.0300
Between: More, less risk averse	0.891	0.0297

Table 6: Coefficient Ratios of Links and Isolates Pooled Subgraph Generation Model: Risk Sharing Network. Sample size = 49536 dyads.

Model(s), Subgraph	Ratio	Std. Err.
Preferences/Baseline		
Within: Less risk averse	1.281	0.0213
Within: More risk averse	0.768	0.0192
Between: More, less risk averse	0.944	0.0198
Abridged models, total sample size = 49536 dyads		

Table 7: Coefficient Ratios of Links and Isolates Pooled Subgraph Generation Model: Community Network. Sample size = 49536 dyads.

7 Welfare Implications of Assortative Matching

To quantify the welfare effect of assortative matching, I compare among four scenarios. I list these scenarios here from high to low aggregate welfare:

A. The optimal scenario: The planner's optimum with equal numbers of types. No assortative matching.

B. The community scenario: takes the degree of assortative matching implied by community SUGM estimates. Some assortative matching.

C. The bilateral scenario: takes the degree of assortative matching implied by bilateral SUGM estimates. slightly more assortative matching than the community scenario

D. The worst case scenario: complete assortative matching.

Qualitatively, these scenarios are depicted in Figures 12, 13, 14, and 15.

To look at these counterfactual scenarios, I simulate type allocation using a binomial data generating process. The scenarios differ by the probability of "success" in the binomial process. Using the results from our SUGMs I am able to construct implied membership of communities. In the special case of communities, where all community members form a clique, I am able to directly estimate the ratio of coefficients. This is also useful because it can give us an analytic expression for the average proportion of the majority type each community. By construction, the majority type will be type 1 in about half of the communities and type 2 in the other half.[20] Using simplifying assumptions (covered in detail in Appendix D.3) I am able to express the average proportion of the majority type, p^U.

$$p^U = 0.5 + 0.5 \times \sqrt{1 - \left(\frac{N-G}{N-1}\right)\left(\frac{\tilde{\beta}_{L,1,2}}{\tilde{\beta}_{ra}}\right)} \tag{27}$$

To see a visualization of equation 27 in action, see Figures 12, 13, 14, and 15.

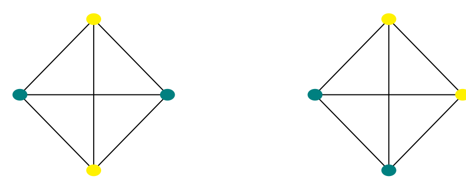


Figure 12: Scenario A, No Assortative Matching: optimal composition of risk pooling communities. Yellow is more risk averse, teal is less risk averse. $\tilde{\beta}^C_{L,1,2} = 0.5$ and $p^U = 0.5$.

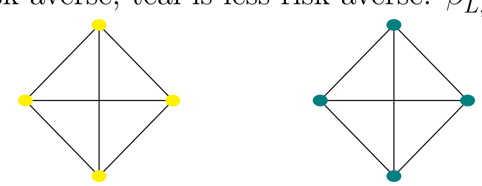


Figure 13: Scenario D, Complete Assortative Matching: a worst case composition of risk pooling communities. Yellow is more risk averse, teal is less risk averse. $\tilde{\beta}^C_{L,1,2} = 0$ and $p^U = 1$.

Once I obtain p^U for a scenario, it becomes the basis for a simulation of communities. Each

[20] I express this ratio as

$$\frac{\tilde{\beta}_{1,2}}{\tilde{\beta}_L} = \frac{\left(\sum_{g=1}^{G} N_{1g}N_{2g}\right) \Big/ N_1 N_2}{\left(\frac{\sum_{g=1}^{G} N_g(N_g-1)}{2}\right) \Big/ \left(\frac{N(N-1)}{2}\right)}.$$

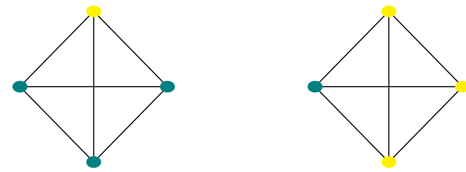


Figure 14: Scenario B, Some assortative matching: a suboptimal composition of risk pooling communities. Yellow is more risk averse, teal is less risk averse. $\tilde{\beta}^{C}_{L,1,2} = 0.375$ and $p^U = 0.75$.

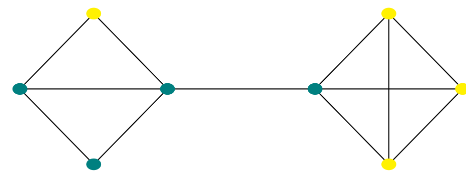


Figure 15: Scenario C, Some assortative matching in a risk sharing network. Yellow is more risk averse, teal is less risk averse. $\tilde{\beta}^{C}_{L,1,2} = 0.3125$ and $p^U = 0.8061$.

simulation proceeds as follows. First, I remove all individuals who do not have preference data, or who are not risk averse and discard resulting "communities of one." Second, I randomly sort communities into roughly equally populous type 1 or type 2 majority bins.[21] Third, after communities have been assigned to type 1 or type 2 majority bins, I simulate community membership as a N_g draws from a binomial distribution with $\bar{p}^U$ with success being defined as a type 1 agent or a type 2 agent, respectively. Finally, I compute the value function for each community and average welfare across all four villages. I simulate community membership 50000 times, compute the value functions, and plot the results in Figure 16.

	less Scenario		
Scenario	B. Community	C. Bilateral	D. Worst Case
A. Optimal	4.60	5.37	19.66
B. Community		0.76	15.06
C. Bilateral			14.29

Table 8: Differences in per capita loss from risk between scenarios. Each entry is column less row. Differences are in PPP Dollars.

[21] Directly minimizing the difference in membership in type 1 and type 2 majority communities is an np-hard problem and requires a workaround. To assign communities, first I sort the communities into a random order. I designate a bin of type 1 majority, and one for type 2 majority and a I construct a running membership sum for each bin. I add a community to bin 1 when $sum1 \leq sum2$ and to bin 2 otherwise and proceed until all communities have been added.

A. With no assortative matching, the optimal scenario has type 1 and type 2 agents each chosen at 0.5. The average loss per capita in this scenario is $-136.76 PPP$

B. The community scenario has some assortative matching, as $R_{1,2} = 0.944$. I compute $p^U = 0.754$ under this scenario. The average loss per capita due to risk is -141.38 in this scenario.

C. The network scenario has slightly more assortative matching, as $R_{1,2} = 0.944$. I compute $p^U = 0.774$ under this scenario. The average loss due to risk is -142.13 in this scenario.

D. Finally, in the worst case scenario, there is complete assortative matching, so communities chosen as type 1 majority are completely type 1 and communities chosen as type 2 are completely type 2. The average loss due to risk is -156.43 in this scenario.

The average differences in scenarios are presented in Table 8. Due to relatively similar degrees of assortative matching in the bilateral and the community scenario, I see relatively similar degrees of welfare. However, given larger differences in the degree of assortative matching, there could be potentially large reductions in welfare. These are bounded, holding community size and risk aversion constant, by the worst case scenario.

8 Conclusion

8.1 Summary

In this paper, I explore assortative matching on risk preferences as a barrier to covariate risk sharing. I characterize optimal covariate risk sharing with heterogeneous types in subvillage communities and to test if observed networks "set the table" for this type of risk sharing. I construct a model of covariate risk sharing with heterogeneous risk preferences. In this model, agents benefit from connecting to other risk agents who have risk preferences unlike

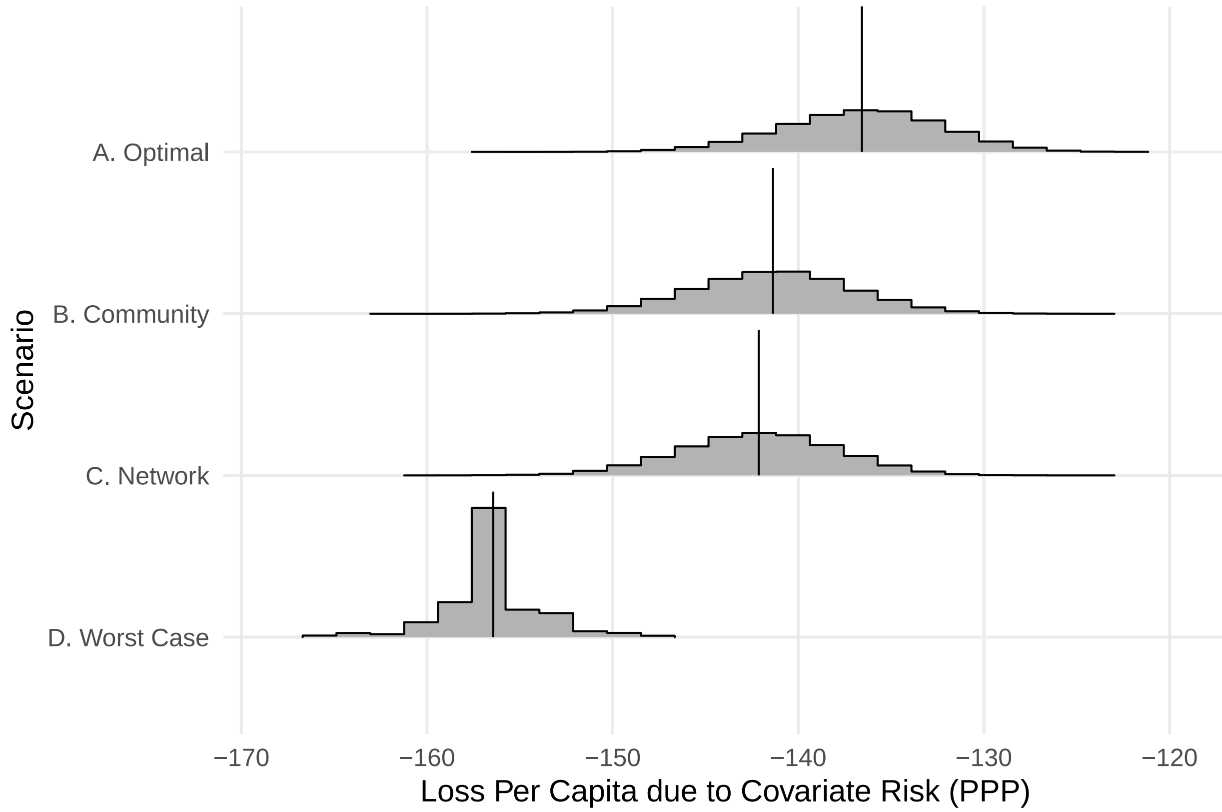


Figure 16: Histograms plots of welfare losses due to risk from 50000 simulations, scenario means are in black.

their own. In the community setting, I find that with less and more risk averse types, the optimal allocation of types to communities reflects the population distribution of types. That is, each community should have the same roughly the same proportion of more and less risk averse types as the village. This optimal allocation gives us a situation that sets the table for optimal risk sharing to take place. Optimal allocation of types to communities corresponds to a case of no assortative matching.

Using data on risk sharing, I estimate that individuals tend to match with those people who have similar degree of risk aversion. This tends to be driven by links within kinship networks. Furthermore, this assortative matching driven by within links of low risk aversion types. In essence, low risk aversion types have both higher degree overall and a preference to link to their own type. When looking at the community network, which bounds the scope of risk pooling, I do not see the same evidence of assortative matching, even within the kinship network. While estimates vary, the magnitude of assortative matching fall in the community network.

Taking seriously the model of covariate risk sharing derived earlier, I simulate welfare outcomes and find that the magnitude of assortative matching is small from the perspective of ex ante economic welfare. While I find large reductions in ex ante welfare due to covariate risk, the losses due to assortative matching are small relative to the losses due to the relatively small size of risk pooling communities. I estimate that on average \$141.38 PPP is lost due to covariate risk relative to a case where this could be fully insured. The optimal scenario averts only \$19.66 PPP of these losses relative to the worst case scenario. Additionally, risk pooling networks are relatively close to optimal, when community size is held constant. I estimate the optimal scenario would avert only \$4.60 PPP over the same period when compared to the actual distribution of types to communities.

8.2 Limitations

It's valuable to address a few limitations which pertain largely to the estimation of the network formation models and the welfare simulations. First, while the the results measure assortative matching on risk preferences in equilibrium, there is not an obvious causal interpretation for the coefficients. In particular, even if the selection on observables approach manages omitted variable bias, reverse causality remains a thorn. Do people match with those who have similar risk preferences, or do they have similar risk preferences because they match? While the preferred interpretation of a model of network formation would be the former, it is important to recognize that the latter remains plausible.[22]

Second, measures of risk aversion are upper and lower bounded. In this data, about 25% of individuals who are surveyed about their preferences choose the most risk averse options available on all questions. Thus, we should be cognizant that at least some of these agents have their degree of risk aversion underestimated. Moreover, this is meaningful within the

[22]See, for example Lucks et al. (2020), where randomly matched adolescents align risky choices with their match.

theoretical model. In particular, the greater the degree of risk aversion, the greater the losses for a given level of assorative matching on risk preferences. Figure 18 in the Appendix depicts this point. Based on this line of reasoning, it is plausible that this approach underestimates the losses due to assortative matching.

Third, and finally, the story told here about assortivity is certainly incomplete. In particular, the omission of formal financial markets looms large. While the simple story of risk pooling told centers on assortivity in risk aversion, it is quite plausible that assortivity on other dimensions including savings or access to credit could similarly impact ones ability to share covariate risk. Where risk aversion correlates with these other factors, risk sharing depends even more on the degree of assortivity in society.

8.3 Discussion and Future Work

How can we square the empirical results on assortative matching with the theory above? Does the failure to achieve zero assortative matching suggest that individuals are failing to maximize utility? I would not go so far. In particular, the model presented here abstracts away from issues of asymmetric information that tend to plague risk sharing. Models where agents can take risky actions might provide an incentive for this type of assortative matching. Indeed, this logic is reflected in theoretical models where asymmetric information over risky actions and heterogeneity in risk aversion and/or risk endowments is present (Attanasio et al., 2012; Jaramillo et al., 2015; Wang, 2015; Gao and Moon, 2016). This suggests that future avenues need balance the apparent substitution between idiosyncratic and covariate risk sharing.

A final point, and one avenue for future exploration arises from a problem of the empirical setting: less risk averse agents tend to be more popular in risk sharing networks than their more risk averse peers. This result is unintuitive from the perspective of theory. For example, Jaramillo et al. (2015) finds that the core of risk sharing networks is made up of the most risk averse in the village. It also unintuitive when we consider risk sharing as an coping strategy for those excluded from formal risk management tools. We would expect (and possibly hope) that those who are more risk averse to demand more insurance and thus find themselves more deeply embedded in these risk sharing networks. To the contrary, more risk averse agents tend to find themselves distant from the center of networks, with fewer connections. This feature of network formation yields a puzzle and a problem for future research.

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A Additional Tables

Table 9: Dyadic Regression: Risk Sharing Network with Controls

	(1)	(2)	(3)	(4)	(5)
$\lvert\eta_i - \eta_j\rvert$	-0.00164	-0.0107*	0.00231	-0.0110*	-0.00950
	(-0.38)	(-2.37)	(0.52)	(-2.48)	(-1.92)
$\eta_i + \eta_j$		-0.0102*		-0.0150***	-0.0150***
		(-2.15)		(-3.36)	(-3.36)
family_{ij}			0.399***	0.400***	0.408***
			(25.33)	(25.57)	(23.77)
$\text{family}_{ij} \times \lvert\eta_i - \eta_j\rvert$					-0.00851
					(-0.92)
Village FE	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
N	65102	65102	65102	65102	65102
R^2	0.2322	0.2329	0.3445	0.3460	0.3461

t statistics in parentheses

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

Table 10: Dyadic Regression: Community Network with Controls

	(1)	(2)	(3)	(4)	(5)
$\|\eta_i - \eta_j\|$	0.000144	0.000717	0.00139	0.000631	0.000547
	(0.04)	(0.20)	(0.39)	(0.18)	(0.14)
$\eta_i + \eta_j$		0.000647		-0.000861	-0.000863
		(0.21)		(-0.27)	(-0.27)
family_{ij}			0.126***	0.126***	0.126***
			(8.21)	(8.22)	(7.23)
$\text{family}_{ij} \times \|\eta_i - \eta_j\|$					0.000486
					(0.05)
Village FE	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
N	65102	65102	65102	65102	65102
R^2	0.2394	0.2394	0.2628	0.2628	0.2628

t statistics in parentheses.

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

Table 11: Dyadic Logistic Regression: Bilateral Risk Sharing Network

	(1)	(2)	(3)	(4)	(5)
$\|\eta_i - \eta_j\|$	-0.0617	-0.127**	-0.0179	-0.135**	-0.110
	(-1.09)	(-2.66)	(-0.30)	(-2.76)	(-1.81)
$\eta_i + \eta_j$		-0.0752		-0.135***	-0.136***
		(-1.89)		(-3.34)	(-3.34)
family_{ij}			2.511***	2.535***	2.618***
			(31.12)	(31.87)	(26.04)
$\text{family}_{ij} \times \|\eta_i - \eta_j\|$					-0.0850
					(-1.34)
Village FE	Yes	Yes	Yes	Yes	Yes
N	71052	71052	71052	71052	71052

t statistics in parentheses.

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

Table 12: Dyadic Logistic Regression: Community Network

	(1)	(2)	(3)	(4)	(5)
$\lvert\eta_i - \eta_j\rvert$	-0.0942	-0.0907	-0.0483	-0.0684	-0.0814
	(-1.34)	(-1.22)	(-0.71)	(-0.95)	(-0.76)
$\eta_i + \eta_j$		0.00404		-0.0235	-0.0235
		(0.07)		(-0.43)	(-0.43)
family_{ij}			2.003***	2.004***	1.978***
			(16.05)	(16.08)	(12.38)
$\text{family}_{ij} \times \lvert\eta_i - \eta_j\rvert$					0.0278
					(0.26)
Village FE	Yes	Yes	Yes	Yes	Yes
N	71052	71052	71052	71052	71052

t statistics in parentheses

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

Table 13: Links and Isolates Pooled Subgraph Generation Model: Risk Sharing Network with Surveyed and Non-surveyed Network Members.

Feature	Count	Potential	Sample size	Coef.	Std. Err.
Isolates:					
Not surveyed	36	96	631	0.375	0.0193
Surveyed	54	535	631	0.1009	0.012
Within links:					
Not surveyed	20	1133	49536	0.0177	0.0006
Surveyed	1367	35526	49536	0.0385	0.0009
Between links:					
Surveyed, not	221	12877	49536	0.0172	0.0006

Table 14: Links and Isolates Pooled Subgraph Generation Model: Community Network with Surveyed and Non-surveyed Network Members.

Feature	Count	Potential	Sample size	Coef.	Std. Err.
Isolates:					
Not surveyed	39	96	631	0.4062	0.0196
Surveyed	77	535	631	0.1439	0.014
Within links:					
Not surveyed	42	1133	49536	0.0371	0.0008
Surveyed	3108	35526	49536	0.0875	0.0013
Between links:					
Surveyed, not	703	12877	49536	0.0546	0.001

Table 15: Pooled Subgraph Generation Model with Links and Isolates and Type: Surveyed. Network size = 631.

Feature	Count	Potential	Sample size	Coef.	Std. Err.
Isolates:					
Surveyed	50	535	631	0.0935	0.0116
Not surveyed	35	96	631	0.3646	0.0192
Within links:					
Surveyed	1535	35526	49536	0.0432	0.0009
Not surveyed	20	1133	49536	0.0177	0.0006
Between links:					
Surveyed, not	247	12877	49536	0.0192	0.0006

Table 16: Pooled Subgraph Generation Model using Community Graph with Links and Isolates and Type: Surveyed. Network size = 631.

Feature	Count	Potential	Sample size	Coef.	Std. Err.
Isolates:					
Surveyed	71	535	631	0.1327	0.0135
Not surveyed	39	96	631	0.4062	0.0196
Within links:					
Surveyed	3411	35526	49536	0.096	0.0013
Not surveyed	38	1133	49536	0.0335	0.0008
Between links:					
Surveyed, not	653	12877	49536	0.0507	0.001

Table 17: Pooled Subgraph Generation Model with Links and Isolates and Type: Preferences. Network size = 631.

Feature	Count	Potential	Sample size	Coef.	Std. Err.
Isolates:					
Less risk averse	21	236	631	0.089	0.0113
More risk averse	19	217	631	0.0876	0.0113
Risk loving	10	82	631	0.122	0.013
Not surveyed	35	96	631	0.3646	0.0192
Within links:					
Less risk averse	471	7511	49536	0.0627	0.0011
More risk averse	203	6223	49536	0.0326	0.0008
Risk Loving	36	814	49536	0.0442	0.0009
Not surveyed	20	1133	49536	0.0177	0.0006
Between links:					
Less, more risk averse	478	11738	49536	0.0407	0.0009
Less risk averse, risk loving	192	4765	49536	0.0403	0.0009
More risk averse, risk loving	155	4475	49536	0.0346	0.0008
Less risk averse, not surveyed	146	5879	49536	0.0248	0.0007
More risk averse, not surveyed	75	5057	49536	0.0148	0.0005
Risk loving, not surveyed	26	1941	49536	0.0134	0.0005

Table 18: Pooled Subgraph Generation Model using Community Graph with Links and Isolates and Type: Preferences. Network size = 631.

Feature	Count	Potential	Sample size	Coef.	Std. Err.
Isolates:					
Less risk averse	36	236	631	0.1525	0.0143
More risk averse	21	217	631	0.0968	0.0118
Risk loving	14	82	631	0.1707	0.015
Not surveyed	39	96	631	0.4062	0.0196
Within links:					
Less risk averse	991	7511	49536	0.1319	0.0015
More risk averse	475	6223	49536	0.0763	0.0012
Risk Loving	64	814	49536	0.0786	0.0012
Not surveyed	38	1133	49536	0.0335	0.0008
Between links:					
Less, more risk averse	1171	11738	49536	0.0998	0.0013
Less risk averse, risk loving	379	4765	49536	0.0795	0.0012
More risk averse, risk loving	331	4475	49536	0.074	0.0012
Less risk averse, not surveyed	356	5879	49536	0.0606	0.0011
More risk averse, not surveyed	229	5057	49536	0.0453	0.0009
Risk loving, not surveyed	68	1941	49536	0.035	0.0008

Table 19: Links and Isolates Pooled Subgraph Generation Model: Risk Sharing Network with Risk Preferences

Feature	Count	Poten.	S. size	Coef.	Std. Err.
Isolates:					
Less risk averse	22	236	631	0.0932	0.0116
More risk averse	19	217	631	0.0876	0.0113
Risk loving	13	82	631	0.1585	0.0145
Not surveyed	36	96	631	0.375	0.0193
Within links:					
Less risk averse	421	7511	49536	0.0561	0.001
More risk averse	186	6223	49536	0.0299	0.0008
Risk loving	33	814	49536	0.0405	0.0009
Not surveyed	20	1133	49536	0.0177	0.0006
Between links:					
Less, more risk averse	423	11738	49536	0.036	0.0008
Less risk averse, risk loving	163	4765	49536	0.0342	0.0008
More risk averse, risk loving	141	4475	49536	0.0315	0.0008
Less risk averse, not surveyed	132	5879	49536	0.0225	0.0007
More risk averse, not surveyed	66	5057	49536	0.0131	0.0005
Risk loving, not surveyed	23	1941	49536	0.0118	0.0005

Table 20: Links and Isolates Pooled Subgraph Generation Model: Community with Risk Preferences

Feature	Count	Poten.	S. size	Coef.	Std. Err.
Isolates:					
Less risk averse	38	236	631	0.161	0.0146
More risk averse	22	217	631	0.1014	0.012
Risk loving	17	82	631	0.2073	0.0161
Not surveyed	39	96	631	0.4062	0.0196
Within links:					
Less risk averse	893	7511	49536	0.1189	0.0015
More risk averse	444	6223	49536	0.0713	0.0012
Risk Loving	59	814	49536	0.0725	0.0012
Not surveyed	42	1133	49536	0.0371	0.0008
Between links:					
Less, more risk averse	1028	11738	49536	0.0876	0.0013
Less risk averse, risk loving	373	4765	49536	0.0783	0.0012
More risk averse, risk loving	311	4475	49536	0.0695	0.0011
Less risk averse, not surveyed	379	5879	49536	0.0645	0.0011
More risk averse, not surveyed	248	5057	49536	0.049	0.001
Risk loving, not surveyed	76	1941	49536	0.0392	0.0009

B Additional Figures

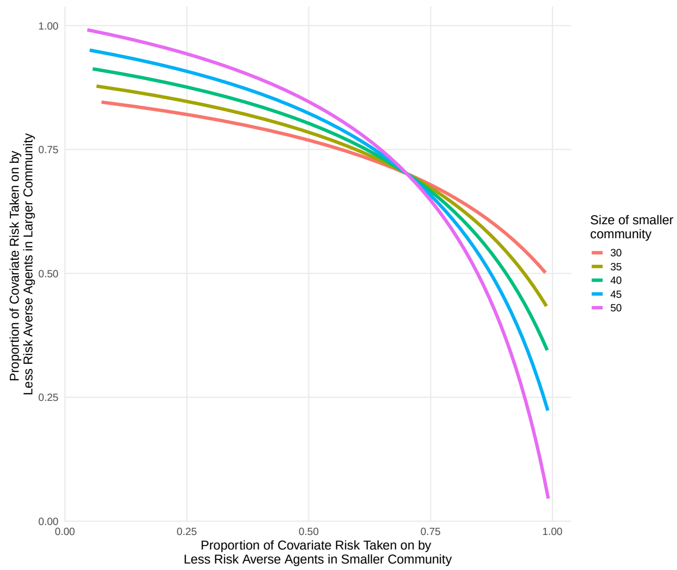

Figure 17: A Risk Management Frontier: Proportion of Covariate Risk Taken on by Less Risk Averse Agents in Communities. From top left to bottom right, type 1 agents move from larger community to smaller.

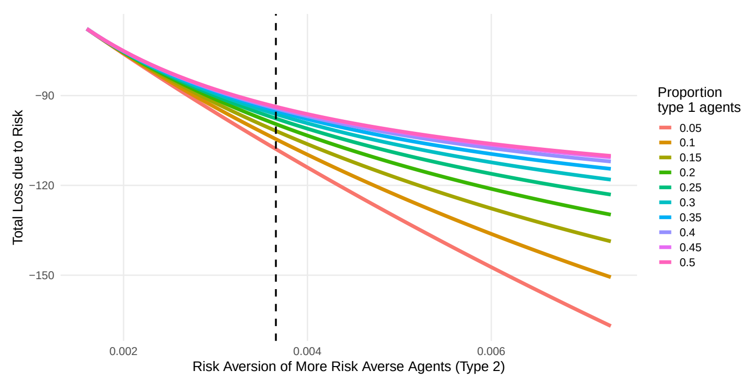

Figure 18: Greater risk aversion increases the welfare impact of assortative matching. As risk aversion increases villages with greater assorative matching will suffer more than those without. However, the delta between assortative is subject to diminishing marginal losses. The dashed vertical line indicates the measured degree of risk aversion among type 2 agents.

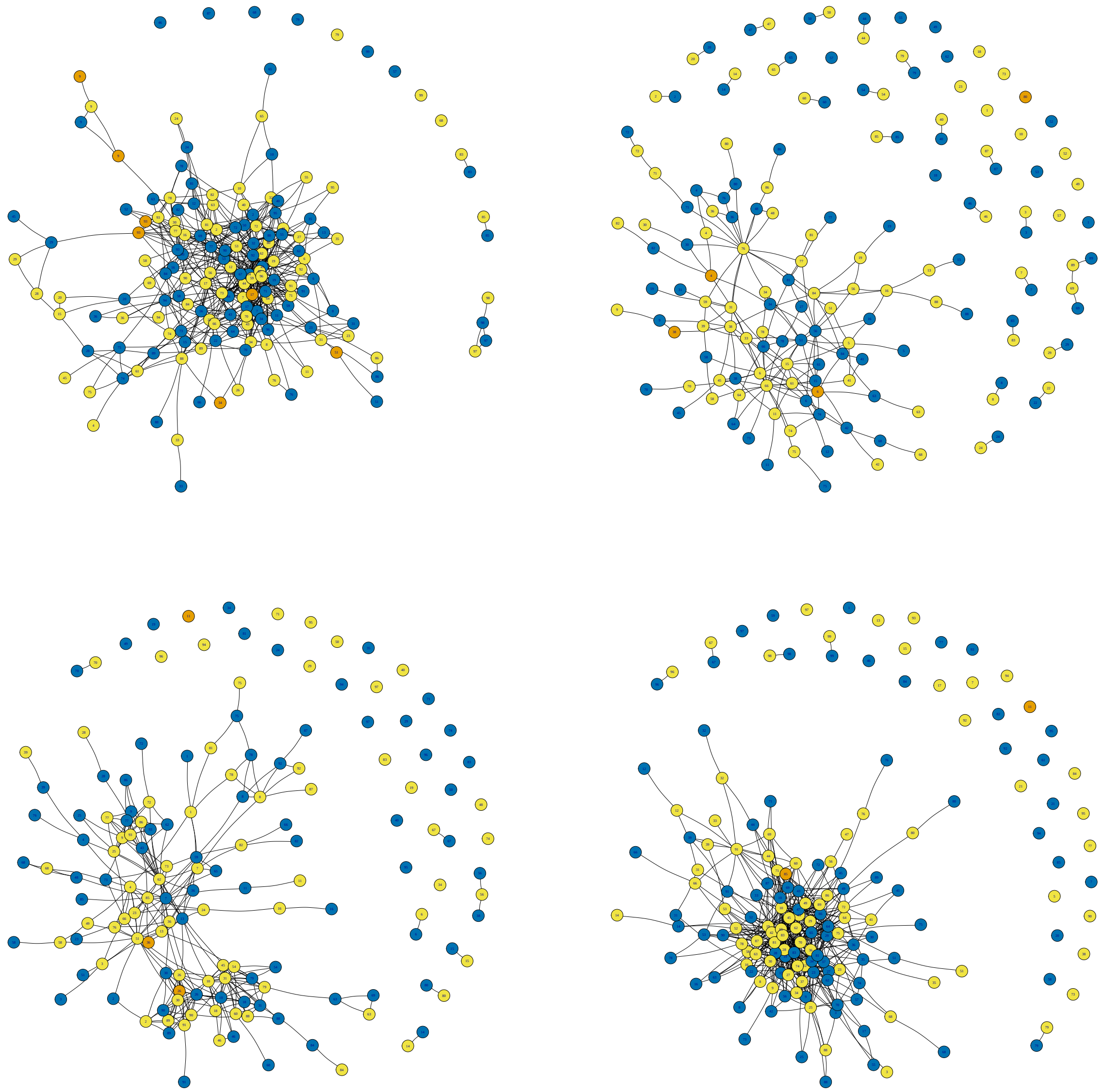

Figure 19: Risk Sharing Networks in Darmang (top left), Pokrom (top right), Oboadaka (bottom left), and Konkonuru (bottom right) with spouses (color = spouse type) and household numbers.

C Theoretical Appendix

C.1 Risk Sharing in Communities

C.1.1 Feasibility of Risk Sharing

Due to constraints 3, 4 and 5, budget constraints bind at the community level. To see this, I sum up the two types using weights:

$$
\begin{aligned}
pc_{1i} + (1-p)c_{2i} &\leq \theta \left(\frac{1}{N} \sum_{i=1}^{N} \tilde{y}_i + \tilde{y}_v \right) + p\lambda_1 \\
&\qquad + (1-\theta) \left(\frac{1}{N} \sum_{i=1}^{N} \tilde{y}_i + \tilde{y}_v \right) + (1-p)\lambda_2 \\
&\leq \frac{1}{N} \sum_{i=1}^{N} \tilde{y}_i + \tilde{y}_v + 0 \\
N_1 c_{1i} + N_2 c_{2i} &\leq \sum_{i=1}^{N} \tilde{y}_i + N\tilde{y}_v.
\end{aligned}
$$

Hence total consumption shocks to types 1 and 2 are bounded by total income shocks and informal insurance is feasible.

C.1.2 Expected Utility

Because shocks are normally distributed, expected utility for both types is equivalent to maximizing the mean-variance representation This can be seen in Sargent (1987).

$$E(U(c_{\ell i})) = E(c_{\ell i}) - \frac{\eta_{\ell i}}{2} Var(c_{\ell i})$$

Also note CARA is an increasing function in consumption, so in all states of the world the agent consume all income and transfers available. Expected consumption for type 1 is $E(c_{1i}) = \lambda_{1i}$ and for type 2, $E(c_{2i}) = \lambda_{2i}$. Variance for the two types can be computed:

$$Var(c_{1i}) = \left(\frac{\theta}{p}\right)^2 \left(\frac{\sigma^2}{N} + \nu^2\right) \quad \text{and} \quad Var(c_{2i}) = \left(\frac{1-\theta}{1-p}\right)^2 \left(\frac{\sigma^2}{N} + \nu^2\right).$$

So then I write expected utility

$$E(U(c_{1i})) = \lambda_{1i} - \frac{\eta_{1i}}{2} \left(\frac{\theta}{p}\right)^2 \left(\frac{\sigma^2}{N} + \nu^2\right) \quad \text{and} \quad E(U(c_{2i})) = \lambda_{2i} - \frac{\eta_{2i}}{2} \left(\frac{1-\theta}{1-p}\right)^2 \left(\frac{\sigma^2}{N} + \nu^2\right).$$

For ease of notation, I define $\sigma_c^2 = \frac{\sigma^2}{N} + \nu^2$. and note that the utility of the the more risk averse agents when only idiosyncratic risk is pooled is equal to

$$EU_0 = -\frac{\eta_{2i}}{2}\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right).$$

C.1.3 Solving the Lagrangian

I construct the Lagrangian retaining constraints 2 and 5 (with a_2 and a_3 as multipliers, respectively) and incorporate the consumption constraints into expected utlity.

$$\mathcal{L} = \lambda_1 - \frac{\eta_1}{2}\frac{\theta^2}{p^2}\sigma_c^2 + a\left(\lambda_2 - \frac{\eta_2}{2}\frac{(1-\theta)^2}{(1-p)^2}\sigma_c^2 + \frac{\eta_2}{2}\sigma_c^2\right) + b\left(p\lambda_1 + (1-p)\lambda_2\right)$$

The first order conditions are as follows:

$$\frac{\partial\mathcal{L}}{\partial\lambda_1} = 1 + bp = 0 \tag{28}$$

$$\frac{\partial\mathcal{L}}{\partial\lambda_2} = a + b(1-p) = 0 \tag{29}$$

$$\frac{\partial\mathcal{L}}{\partial\theta} = \frac{-\eta_1\theta\sigma_c^2}{p^2} + a_2\left(\frac{\eta_2(1-\theta)\sigma_c^2}{(1-p)^2}\right) \tag{30}$$

$$\frac{\partial\mathcal{L}}{\partial a} = \lambda_2 - \frac{\eta_2}{2}\left(\frac{1-\theta}{1-p}\right)^2\sigma_c^2 + \frac{\eta_2}{2}\sigma_c^2 = 0 \tag{31}$$

$$\frac{\partial\mathcal{L}}{\partial b} = p\lambda_1 + (1-p)\lambda_2 = 0 \tag{32}$$

Using FOC 28 I note that $b = -\frac{1}{p}$. Likewise, using FOC 29 I note that $a = \frac{1-p}{p}$. Rearranging FOC 31,

$$\lambda_2 = -\frac{\eta_2}{2}\left(1 - \left(\frac{1-\theta}{1-p}\right)^2\right)$$

I rearrange FOC 32 and substitute in FOC 31:

$$\lambda_1 = -\frac{1-p}{p}\lambda_2 = \frac{1-p}{p}\frac{\eta_2}{2}\left(1 - \left(\frac{1-\theta}{1-p}\right)^2\right)$$

Finally, I simplify FOC 30 to find θ:

$$\begin{aligned}
\frac{\eta_1 \theta \sigma_c^2}{p^2} &= \frac{1-p}{p}\left(\frac{\eta_1(1-\theta)\sigma_c^2}{(1-p)^2}\right) \\
\left(\frac{\eta_1}{\eta_2}\right)\left(\frac{1-p}{p}\right) &= \frac{1-\theta}{\theta} \\
\frac{1}{\theta} &= \left(\frac{\eta_1}{\eta_2}\right)\left(\frac{1-p}{p}\right) + 1 \\
\theta &= \frac{p\eta_2}{(1-p)\eta_1 + p\eta_2}
\end{aligned}$$

Thus only if either $\eta_1 = 0$ (type 1 is risk neutral, which we've assumed is not true) or $p = 1$, $\theta = 1$. Hence, covariate risk will not taken on fully by the less risk averse agents. Note that

$$\begin{aligned}
(1-\theta)^2 &= \left(1 - \frac{p\eta_2}{(1-p)\eta_1 + p\eta_2}\right)^2 \\
&= \left(1 - \frac{(1-p)\eta_1}{(1-p)\eta_1 + p\eta_2}\right)^2 \\
&= \frac{(1-p)^2\eta_1^2}{((1-p)\eta_1 + p\eta_2)^2}
\end{aligned}$$

So then

$$\lambda_2 = -\frac{\eta_2}{2}\left(1 - \frac{\eta_1^2}{((1-p)\eta_1 + p\eta_2)^2}\right)$$

C.1.4 Value Functions

I compute the value functions for type 1 and type 2 individuals. Type 1:

$$\begin{aligned}
V_1(p, \eta_1, \eta_2) &= E(U(c_1 i)|\theta^*(p), \lambda_1^*(p)) \\
&= \lambda_1^* - \frac{\eta_1}{2}\left(\frac{\theta^*(p)}{p}\right)^2 \sigma_c^2 = \lambda_1^* - \frac{\eta_1}{2}\left(\frac{p\eta_2}{((1-p)\eta_1 + p\eta_2)p}\right)\sigma_c^2 \\
&= \lambda_1^* - \frac{\eta_1}{2}\left(\frac{\eta_2}{((1-p)\eta_1 + p\eta_2)}\right)\sigma_c^2 \\
&= \frac{\eta_1}{2}\left(\frac{1-p}{p}\right)\left(1 - \left(\frac{\eta_1}{(1-p)\eta_1 + p\eta_2}\right)^2\right) - \frac{\eta_1}{2}\left(\frac{\eta_2}{(1-p)\eta_1 + p\eta_2}\right)^2 \sigma_c^2
\end{aligned}$$

Type 2:

$$\begin{aligned}
V_2(p,\eta_1,\eta_2) &= E(U(c_2 i)|\theta^*(p),\lambda_2^*(p)) \\
&= \lambda_2^*(p) - \frac{\eta_2}{2}\left(\frac{1-\theta^*(p)}{1-p}\right)^2 = \lambda_2^*(p) - \frac{\eta_2}{2}\left(\frac{1-\frac{p\eta_2}{(1-p)\eta_1+p\eta_2}}{1-p}\right)^2 \sigma_c^2 \\
&= \lambda_2^*(p) - \frac{\eta_2}{2}\left(\frac{(1-p)\eta_1+p\eta_2-p\eta_2}{(1-p)((1-p)\eta_1+p\eta_2)}\right)^2 \sigma_c^2 \\
&= \lambda_2^*(p) - \frac{\eta_2}{2}\left(\frac{(1-p)\eta_1+p\eta_2-p\eta_2}{(1-p)((1-p)\eta_1+p\eta_2)}\right)^2 \sigma_c^2 \\
&= \lambda_2^*(p) - \frac{\eta_2}{2}\left(\frac{(1-p)\eta_1}{(1-p)((1-p)\eta_1+p\eta_2)}\right)^2 \sigma_c^2 \\
&= \lambda_2^*(p) - \frac{\eta_2}{2}\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2 \sigma_c^2 \\
&= \ -\frac{\eta_2}{2}\left(1-\frac{\eta_1^2}{((1-p)\eta_1+p\eta_2)^2}\right) - \frac{\eta_2}{2}\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2 \sigma_c^2 \\
&= \frac{\eta_2}{2}\left(1+\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2 (1+\sigma_c^2)\right)
\end{aligned}$$

C.1.5 The Rate of Risk Pooling

One result of the theoretical model is that the proportion of risk taken on by less risk averse individuals in a community in equilibrium is greater than their proportion of the community. To see this, note that since $\eta_1 < \eta_2$ by assumption $p\eta_2 + (1-p)\eta_1 < \ p\eta_2 + (1-p)\eta_2 = \eta_2$. Thus,

$$\theta^*(p,\eta_1,\eta_2) = \frac{p\eta_2}{p\eta_2+(1-p)\eta_1} > \frac{p\eta_2}{\eta_2} = p$$

D Empirical Appendix

D.1 Community Detection

D.1.1 Other Approaches

While the walktrap algorithm features good properties for community detection, it is by no means the only option. One appealing approach to assign households to communities is *edge betweenness* community detection. This algorithm is appealing because it takes advantage of information bottlenecks in networks, connecting naturally to the types of asymmetric information problems that constrain risk sharing (Girvan and Newman, 2004). For more on edge betweenness, see D.1.2. For large networks (like mobile money transaction networks) there may be better methods from the perspective of computation speed. However, detected communities from a given algorithm may not scale well to larger networks if community size grows with network size. An iterated min cut algorithm may fall closer to the conditions that create *ex post* risk sharing islands Ambrus et al. (2014).

D.1.2 Edge Betweenness

Another intuitive approach to finding communities hinges on information in networks. Edge betweenness measures how central an edge is in a network by counting which nodes it lies between. In particular, if edge kl lies on the shortest path from i to j edge kl is awarded a unit of edge betweenness. Summing up all of these awards from all pairs of nodes i and j, I get the edge betweenness for edge kl. I can think of edges with high betweenness as relationships in the risk sharing network where both individuals knowledge of the other individual and the individuals beyond them comes directly through that individual. There is a great deal of potential to broker information over these links but because of frictions due to adverse selection, hidden income, and various types of moral hazard, individuals will be hesitant to share risk with those who they do not have good information about.

The algorithm is named because it calculates the *betweenness centrality* of all edges in the network and deletes those edges with highest centrality. Edge betweenness centrality is a measure of how central an edge is in a network based on who relies on that edge connect to other portions of the network. In order to compute this measure, compute all shortest paths between nodes on a network. Then, count of the number of shortest paths passing through each edge of interest (in the case multiple paths tie for shortest path for two nodes, a partial count is awarded across the edges in these paths). Intuitively, betweenness centrality is often used as a measure the potential for brokerage. In this case, I can think of information flow being costly in the link that has high betweenness centrality because of the gatekeeper on each side. This would create a specific rationale for these communities as risk sharing units, then. One issue with edge betweenness is that weighted versions of the algorithm may not interpret weights in an intuitive manner for our application. In particular larger capacity connections are lower cost and hence have more least cost paths contributing to betweenness. This will cause these edges to be cut early. Initially I will solve this by supplying inverse weights to the algorithm. At the start of the algorithm, all nodes in a particular component are assigned to the same community. Every time a component breaks into two with the deletion of an edge, the communities membership is reassigned for the nodes in the broken component. After initially computing all edge betweenness centralities, the algorithm works in two steps:

1. Delete the edge with the highest betweenness centrality

2. Recompute the betweenness centrality of remaining edges

This two step process continues until all edges are deleted and thus all nodes reside in their own component and hence community. To choose a final community assignment, the algorithm cuts the dendrogram using a tuning statistic. For this, I have two possible solutions. First, the off the shelf choice in network science is modularity, which measures the internal quality of communities assigned (see Appendix D.1.3 for details). The algorithm cuts of the dendrogram at the assignment with the maximum value of the tuning statistic (Girvan and Newman, 2004). In previous unpublished work, I used edge betweenness community detection to detect risk sharing islands using data from southern India. Alternatively, a regression coefficient measuring the degree of risk sharing in the community assignment could be used to tune the assignment. I leave discussion of this second option until tests of risk sharing have been discussed.

D.1.3 Modularity

To compute modularity let k_i and k_j be the degrees of nodes i and j, respectively. Let m be the number of edges in the graph. The expected number of edges between i and j from this rewiring is equal to $k_i k_j/(2m-1) \approx k_i k_j/2m$ ($2m$ since each link has two "stubs", so to speak). I can then compare this expected number of links between i and j to the actual connections: letting A_{ij} be the ijth entry of the matrix, I take the difference these two numbers:

$$A_{ij} - \frac{k_i k_j}{2m}$$

I can interpret this as connections over expected conditional on node pair degrees. Then, letting c_i be the community membership of node i, connections over expectation are weighted by the function δ:

$$\delta(c_i, c_j) = \begin{cases} 1 & \text{if } c_i = c_j \\ 0 & \text{otherwise} \end{cases}$$

Finally I aggregate to the graph level and normalize by twice the number of links present:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

This serves as an easily computable and straightforward measure of the internal quality of communities (Newman, 2011).

D.2 Approximation of Variance of Ratios

want the ratio of the variance of two coefficients $\tilde{\beta}_{L,s}$ and $\tilde{\beta}_{L,ra}$,

$$Var\left(\frac{\tilde{\beta}_{L,s}}{\tilde{\beta}_{L,ra}}\right) = \left(\frac{\tilde{\beta}_{L,s}}{\tilde{\beta}_{L,ra}}\right)^2 \left(\frac{(\sigma_s)^2}{(\tilde{\beta}_{L,s})^2} - \frac{2Cov(\tilde{\beta}_{L,s}, \tilde{\beta}_{L,ra})}{\tilde{\beta}_{L,s}\tilde{\beta}_{L,s}} + \frac{\sigma_{ra}^2}{\tilde{\beta}_{L,ra}^2}\right)$$

Given that the two coefficients derive from a similar data generating process and measure a similar quantity, it is intuitive that $Cov(\tilde{\beta}_{L,s}, \tilde{\beta}_{L,ra}) > 0$. My priors are that the correlations between these two coefficients would be close to one. Maintaining this assumption, it is conservative to estimate the variance of the ratio by assuming $Cov(\tilde{\beta}_{L,s}, \tilde{\beta}_{L,ra}) = 0$. This assumption leaves us with

$$Var\left(\frac{\tilde{\beta}_{L,s}}{\tilde{\beta}_{L,ra}}\right) = \left(\frac{\tilde{\beta}_{L,s}}{\tilde{\beta}_{L,ra}}\right)^2 \left(\frac{(\sigma_s)^2}{(\tilde{\beta}_{L,s})^2} + \frac{\sigma_{ra}^2}{\tilde{\beta}_{L,ra}^2}\right)$$

D.3 Welfare Simulations

D.3.1 Rate of Between Link Generation

How many connections there are between types in communities? The complete bipartite graphs yields simple counts. A complete bipartite graph with N_{1g} of type 1 and N_{2g} of type 2, will have $N_{1g}N_{g2}$ connections. Thus the total number of actual connections between types within communities is $\sum_{g=1}^{G} N_{1g}N_{2g}$. Additionally, the total number of potential links between types in the entire village graph will be $\left(\sum_{g=1}^{G} N_{1g}\right)\left(\sum_{g=1}^{G} N_{2g}\right) = N_1N_2$. So then

$$\tilde{\beta}_{1,2} = \frac{\sum_{g=1}^{G} N_{1g}N_{2g}}{N_1N_2}$$

I assume equal parts type 1 and type 2 agents, which I impose empirically as well, so then $N_1 = N_2$ and $N_1 + N_2 = N$ so $N_1 = N_2 = \frac{N}{2}$

$$\tilde{\beta}_{1,2} = \frac{\sum_{g=1}^{G} N_{1g}N_{2g}}{\frac{N^2}{2^2}} = \frac{4 \times \sum_{g=1}^{G} N_{1g}N_{2g}}{N^2}$$

$$\tilde{\beta}_{1,2} = 4 \times \sum_{g=1}^{G} \frac{N_{1g}}{N}\frac{N_{2g}}{N} = 4 \times \sum_{g=1}^{G} \frac{N_g p_{1g}}{N}\frac{N_g p_{2g}}{N} = 4 \times \sum_{g=1}^{G} \left(\frac{N_g}{N}\right)^2 p_{1g}p_{2g}$$

For the last equality, recall that $p_{\ell g} = \frac{N_{\ell g}}{N_g}$. I make the (heroic) simplifying assumption that community sizes are the same, hence there's a fixed $\frac{N_g}{N} = \frac{1}{G}$. Additionally, fix $p_{1g} = \bar{p}^U$ and $p_{2g} = \bar{p}^L$ when $p_{1g} \geq p_{2g}$ and vice-versa when $p_{1g} < p_{2g}$ where $\bar{p}^U = 1 - \bar{p}^L$.

$$\tilde{\beta}_{1,2} = \frac{4}{G^2} \times \sum_{g=1}^{G} p_{1g}p_{2g} = \frac{4}{G^2} \times \sum_{g=1}^{G} \bar{p}^U \bar{p}^L$$

Finally, I sum across groups and then rearrange to get an expression for $\tilde{\beta}_{1,2}$

$$\tilde{\beta}_{1,2} = \frac{4}{G}\bar{p}^U \bar{p}^L.$$

D.3.2 Rate of Within Risk Averse Link Generation

The total number of potential links generated is $\frac{N(N-1)}{2}$. With completely connected communities, the number of connections ends up being $\frac{\sum_{g=1}^{G} N_g(N_g-1)}{2}$. So then

$$\tilde{\beta}_L = \frac{\frac{\sum_{g=1}^{G} N_g(N_g-1)}{2}}{\frac{N(N-1)}{2}} = \frac{\sum_{g=1}^{G} N_g(N_g-1)}{N(N-1)}$$

Suppose, as above, that $N_g = \frac{N}{G}$. Then

$$\begin{aligned}\tilde{\beta}_L &= \frac{\sum_{g=1}^{G} \frac{N}{G}(\frac{N}{G} - 1)}{N(N-1)} = \frac{N(\frac{N}{G} - 1)}{N(N-1)} \\ &= \frac{(\frac{N}{G} - 1)}{(N-1)} = \frac{(N-G)}{G(N-1)}.\end{aligned}$$

D.3.3 Ratio of Rates

Based on this, I can express the ratio of the link generation coefficients as an expression relating the proportion in each community to the rate of generation.

$$\begin{aligned}\frac{\tilde{\beta}_{1,2}}{\tilde{\beta}_L} &= \frac{\frac{4}{G}\bar{p}^U \bar{p}^L}{\frac{(N-G)}{G(N-1)}} \\ &= 4\frac{(N-1)}{(N-G)}\bar{p}^U \bar{p}^L\end{aligned}$$

Hence I write:

$$\bar{p}^U \bar{p}^L = \left(\frac{1}{4}\right)\left(\frac{N-G}{N-1}\right)\left(\frac{\tilde{\beta}_{1,2}}{\tilde{\beta}_L}\right)$$

The RHS of the equation lies between 0 and $\frac{1}{4}$. Note that as N becomes large, $\left(\frac{N-G}{N-1}\right) \to 1$, but that this kind of small sample correction does account for the fact that between connections make up a larger share of connections than within connections when loops are omitted. Another way to think of this is when sampling pairs, sampling without replacement only matters when sampling pairs within a type. I can solve the above by using a system of equations where $\bar{p}^U + \bar{p}^L = 1$, and use the quadratic formula to get an analytic solution:

$$(p^U, p^L) = 0.5 \pm 0.5 \times \sqrt{1 - \left(\frac{N-G}{N-1}\right)\left(\frac{\tilde{\beta}_{1,2}}{\tilde{\beta}_L}\right)}.$$