Sharing Covariate Risk in Networks: Theory and Evidence from 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

The economic position of the rural poor is precarious, vulnerable to losses from both idiosyncratic and covariate shocks (Ligon and Schechter, 2003; Günther and Harttgen, 2009; Collins et al., 2010). Idiosyncratic risks include shocks like illness, loss of employment, and theft, or the loss of a family member that are uncorrelated between individuals or households in localities. In contrast, covariate risks like output price and weather shocks are correlated among these individuals or households. Despite the recent adoption of digital financial services in some markets, risk management tools to manage such risks are still missing for many (Demirguc-Kunt et al., 2018). This fact may prevent risk taking which would result in higher incomes over the long term (Elbers et al., 2007; Karlan et al., 2014). In the absence of formal financial markets, informal risk sharing, mediated through social networks, is a common and important method of managing risk (Fafchamps and Lund, 2003; Comola and Fafchamps, 2017).

The classic story of informal risk sharing is as follows: two people are seeking to insure their consumption against idiosyncratic risks. If you lose your job, I pay you; If I lose my job, you pay me. Evidence is often consistent with a high degree of idiosyncratic risk sharing even in light of information asymmetries (Kinnan, 2021). In contrast, sharing of covariate risks is much less explored, despite the fact that most studies are set in rural economies where the role of covariate risk is more prominent (Günther and Harttgen, 2009). When risk preferences are heterogeneous, sharing covariate risk can lead to welfare improvements by shifting risks from more risk averse to less risk averse agents in exchange for a premium (Chiappori et al., 2014).[1] In this story of informal risk sharing, in a bad (overall) 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. In essence, less risk averse agents become miniature insurance companies for their peers.[2]

This story of covariate risk sharing, however, depends critically on the proximity of less and more risk averse agents in social networks. In contrast, there is a tendency to connect to those similar to oneself

[1]With the adoption of mobile money and other digital payment systems in recent years, it is important to delineate this story covariate risk sharing from digitally mediated inter-village risk sharing which might also help cope with locally covariate risk (Jack and Suri, 2014). For those who have adopted mobile money, what we think of as covariate shocks (droughts, flooding, earthquakes) may become become idiosyncratic (Blumenstock et al., 2016; Riley, 2018).

[2]While this paper abstracts away from the specific transactions that might allow for covariate risk sharing, concrete notions of suitable arrangements can be found. For example, the literature on sharecropping places sharecropping as way for a more risk averse renter to pass risk to their less risk averse landlord (Stiglitz, 1974; Braverman and Stiglitz, 1986). Similarly, renters need would need to be more risk averse than landlords (Allen and Lueck, 1995). Sharecropping is relatively common in the context at hand, accounting for about about 50% of rental contracts (Goldstein and Udry, 2008).

in social and economic networks (McPherson et al., 2001). As has been documented experimentally, this pattern of *assortative matching* on risk preferences arises as a barrier to covariate risk sharing (Attanasio et al., 2012). Given the degree of assorative matching on risk preferences found in real world risk sharing networks, what quality 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 econometric models of network formation to rich microdata featuring income shocks, network ties, and risk preferences from a survey in four villages in rural southern Ghana (Barrett, 2009). This setting features prominent correlated 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 (Pons and Latapy, 2005; Newman, 2012). 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) (Putman, 2022). For risk preferences, I back out coefficients of absolute risk aversion using the hypothetical gambles.

To translate my estimates of assorative matching into concrete welfare estimates, I construct a theoretical model of optimal risk pooling in a village setting. In this model, risk is pooled in subvillage groups. While idiosyncratic risk pooling is assumed to be fully shared, a social planner assigns individuals to two risk pooling groups according to their risk aversion to optimally share covariate risk. According to this model, optimal risk pooling happens when the composition of the groups reflects the composition of the village with respect to risk aversion. 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 (Graham, 2020). That is, they prefer to match with individuals who have a similar degree of risk aversion. My preferred specification is is conditional on controlling for the sum of risk aversion. I do so to solve a subtle correlation between popularity and risk aversion present in the data.

However, this evidence is borne out by several additional econometric models, including dyadic logistic regression; Subgraph Generation Models (SUGMs) (Chandrasekhar and Jackson, 2018); Tetrad Logit, a model designed to account such degree heterogeneity Graham (2017); and controlling for a large set of dyadic characteristics.[3] Assortative matching tends to be driven by connections between family members. The SUGMs allow 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 detected communities as the relevant unit of risk sharing, however, I either fail to find evidence of assortative matching on risk preferences or find great attenuation in the degree of assorative matching. Using dyadic regression (with and without controls), dyadic logistic regression, and tetrad logit I fail to provide evidence for assorative matching. Likewise, when estimating the SUGMs, I find that the magnitude of assortative matching is attenuated in the community network *vis a vis* 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, with no assortative matching (b) a community scenario, (c) the bilateral scenario, and (d) a worst case scenario, with complete assortative matching. (a) and (d) are determined by the theoretical model derived earlier, while (b) and (c) derive from empirical estimates from the SUGMs. 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 substantial differences between the optimal and worst case scenario, with the community and bilateral scenarios both falling close to optimal. First, despite the observed assortative matching, I find that the observed networks tend to be close to optimal networks already. I.e., if 0% is the worst case scenario, and 100% is the optimum, observed assortative matching in networks place us 75% of the way to the optimum. As one might expect, the more diverse community networks 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

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

consumption. This suggests that while individuals may be able to do well with the risk management tools they are given, there are still large gains to be had in improved these tools.

This work contributes to the understanding of covariate risk sharing by situating it within the context of local network structure. Recent work has suggested the potential for covariate risk sharing. For example, Chiappori et al. (2014) find considerable heterogeneity in risk preferences under the assumption that risk sharing arrangements are complete within villages. An implication of their model is that less risk averse agents might take on more covariate risk in exchange for some increase in consumption over the long term.[4] By relaxing the assumption of risk sharing at the village level, I am able to examine the relationship between network structure and covariate risk sharing, which I find to be important for welfare derived from risk sharing.

This work also contributes to the empirical study of assortative matching on risk preferences in social networks, and to my knowledge is the first evidence of assortative matching on risk preferences in village risk sharing networks.[5] This reflects estimates from Attanasio et al. (2012) which find assorative matching in a behavioral risk pooling experiment. Beyond replicating these results, the current work both provides evidence of assortative matching on risk preferences in real world risk sharing relationships and in a new country context, strengthening the external validity of this empirical result.[6]

Finally, these results contribute to the greater policy discussion on economic development and globalization. First, growing adoption of financial services in lower and middle income countries may have unintended consequences–positive and negative–on risk sharing networks (Banerjee et al., 2018; Comola and Prina, 2020; Cecchi et al., 2016; Dizon et al., 2019). By quantifying the importance of network structure, I reveal an important facet of the the net welfare effects of access to financial services. Second, as climate change and growing interconnections in trade, financial systems, and other systems may increase the scale of crises (Stiglitz, 2003; Zscheischler et al., 2018; Elliott and Golub, 2022). A greater scale of crises, exemplified by the COVID-19 pandemic, makes such covariate risk sharing all the more dear.

[4] An intuition shared by the theoretical model within as well as the one in Wang (2015).

[5] There is work on assorative matching in other dimensions, such as geography, wealth, religious affiliation, clan membership, and kinship (De Weerdt, 2002; Fafchamps and Gubert, 2007).

[6] Interestingly, these estimates are also consistent with models of assortative matching in the presence of idiosyncratic risk sharing (Attanasio et al., 2012; Jaramillo et al., 2015; Wang, 2015; Gao and Moon, 2016).

2 Theoretical Model

In this section, I build a that 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. I consider 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.

2.1 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.

2.1.1 Setup

Suppose a community of fixed size N that sits within a village. Community member i has exponential utility functions with coefficient of absolute risk aversion η_i:

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

Now, suppose there are low and high risk aversion households, where type and indexed by $\ell = 1, 2$. That is, $\eta_2 > \eta_1 > 0$. N_ℓ is number of individuals of type ℓ, and $p = N_1/N$ characterizes the composition of the group in terms of these types. All households face a shock perfectly correlated at the village level, $\tilde{y}_v$ 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 village 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 $\ell = 1, 2$,

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

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 covariate risk is taken on by less risk averse individuals, when $\theta = p$, covariate 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 (for details, see Appendix B.1.1):

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

I will refer to the special case of $EU_0 = E(U_1(c_{1i}|\theta = p)))$, which simply describes the utility from idiosyncratic risk sharing in absence of covariate risk sharing.

2.1.2 Optimization Problem

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

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

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

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

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

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

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 (for more on these constraints, see Appendix B.1.2).

2.1.3 Solutions and Value Functions

How much covariate risk is shifted to the less risk averse agents? I solve the model, and present this process in Appendix B.1.3. The proportion of covariate risk shared will depend on the risk aversion and proportion of each type:

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

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. Since $\eta_2 > \eta_1$, $\theta^* > p$ (see Appendix B.1.4). This means some degree of covariate risk is shifted to less risk averse individuals. Likewise, unless $\eta_1 = 0$ (we assume it does not) 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 (i.e., risk averse and risk loving types face the same covariate risk), the transfer does not depend on covariate risk. 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:

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

These solutions lead to the the value functions I will use in order to solve the planner's problem. These are

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

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

See Appendix B.1.5, for the derivation of these functions.

2.2 Planner's Problem

2.2.1 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 $p_{g\ell} = \frac{N_{g\ell}}{N_g}$.

2.2.2 Optimization Problem

I state the planner's problem as follows:

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

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

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

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

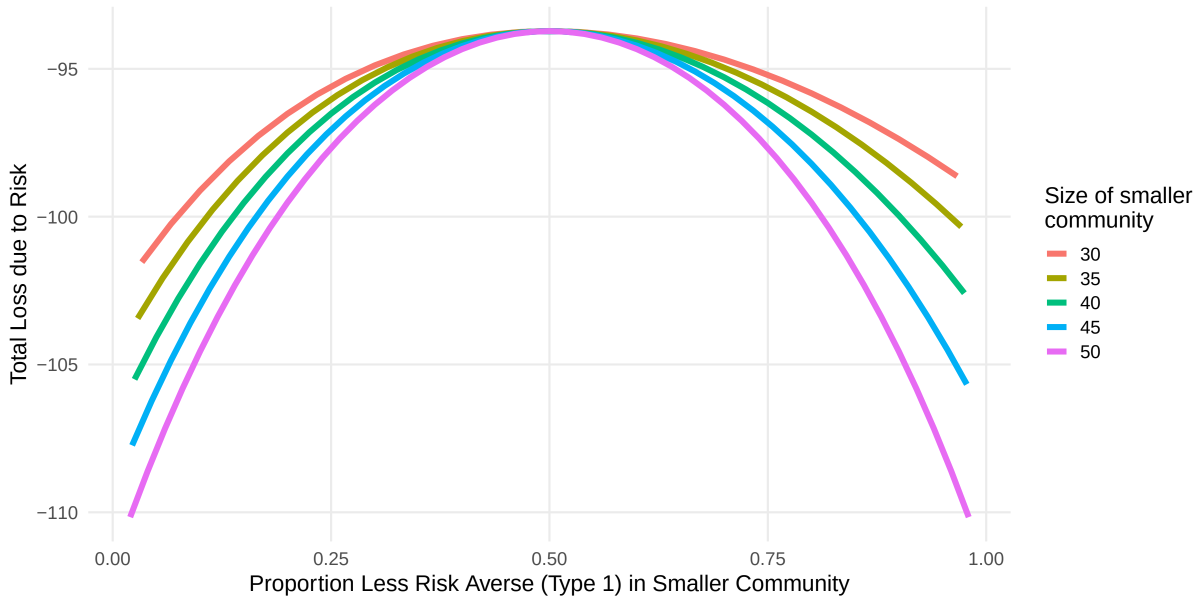


Figure 1: Optimal Allocation of Types Between Unequally Sized Communities

the problem

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

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 average coefficients of absolute risk aversion in my data (see Section 3.2.1 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 9). This is not an artifact of equally sized communities.

For more details, please see Appendix B.2.

3 Data and Context

3.1 Risk and Resilience in Ghana

The data comes from four villages in southern rural Ghana. These villages face significant covariate risk, in particular from the Pineapple export market (Conley and Udry, 2010).[7] Risk management within the villages includes substantial usage of these informal networks (Udry and Conley, 2005; Walker, 2011a).[8] The network data includes 631 individuals across the four villages. The data a also features information about assets, income, and consumption shocks (Barrett, 2009; Walker, 2011a).[9]

3.2 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.

3.2.1 Risk Preferences

I use four hypothetical gambles to measure individuals risk aversion, which ask respondents to choose between a sure payment Y_A and a risky gamble Y_B. These gambles are presented in both the gains and losses domains and with variation in the sure and variable payments. 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 payment Y_A. In the second, the sure payment is held fixed while the upside of the gamble is reduced. The second set of gambles reflect the first set into a losses domain.

To translate these hypothetical gambles into coefficients of risk aversion, I make two assumptions.

[7] Risk management is a key feature of these markets, where farmers use many strategies to manage risk. For example, Suzuki et al. (2011) documents partial vertical integration in Pineapple markets in Ghana, explaining this partial vertical integration as smallholders better equipping themselves to manage this risk through the use of local secondary markets.

[8] A number of other empirical studies have document features of these networks. Vanderpuye-Orgle and Barrett (2009) studies socially invisible members of the villages, and finds that risk pooling does worse that it does for their richer, more socially visible counterparts. Within households, Walker and Castilla (2013) finds spouses behave non-cooperatively, hiding income through gifts to their networks. Finally, some transfers made within these networks may be altruistic, as shown by Nourani et al. (2019).

[9] The survey instrument and further technical details can be found in Walker (2011b).

Table 1: Risk Sharing Network Summary Statistics by Risk Preferences

	More Risk Averse	Less Risk Averse	Risk Loving	No Data
Isolates (Prop.)	0.09	0.09	0.16	0.38
	(0.001)	(0.001)	(0.004)	(0.005)
Average Degree	4.62	6.61	4.79	2.72
	(0.02)	(0.03)	(0.06)	(0.05)
Average Clustering	0.25	0.23	0.23	0.17
	(0.00)	(0.00)	(0.00)	(0.00)
Average Betweenness	85.98	119.53	99.85	43.23
	(0.69)	(0.90)	(2.56)	(1.27)
Average 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. All variables are node level averages. Risk loving are those with $\hat{\eta}_i \leq 0$, less risk averse (type 1) are those with $0 < \hat{\eta}_i < \eta_{\text{split}}$, and more risk averse (type 2) are those with $\hat{\eta}_i \geq \eta_{\text{split}}$, where $\eta_{\text{split}} \approx 0.003$.

First, Y_B is normally distributed and second that individuals exhibit Constant Absolute Risk Aversion (or exponential preferences). From these assumptions I can compute η_i for each menu and individual (Sargent, 1987):

$$\eta_i = \frac{2(E(Y_B) - Y_A)}{V(Y_B)} \tag{15}$$

Finally, to combine these into measures of risk aversion, I average over menus. Details of how each coefficient is computed are available in Appendix C.1. Coefficients of Absolute Risk Aversion are plotted over the risk sharing network for one example village in Figure 2 . Additionally, the distribution of coefficients and definition of types is plotted in Figure 7. 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 $\eta_i < 0$. This accounts for about 20% of the individuals with preferences. I split the remaining risk averse individuals into evenly sized groups of approximately 40% each, with more risk averse individuals being above a cut-point, $\eta_{split} \approx 0.003$.[10]

[10] It is difficult to split into exactly even groups, and the less risk averse group tends to be slightly larger in practice.

3.2.2 Risk Sharing Network

I will draw on graph theory to define 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.[11]

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.[12] If a connection occurs in both networks, I record a connection 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.[13] I present the average degree. Isolates is computed as the proportion of individuals who are not connected to any other individual in the network (so have degree zero). 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).[14] 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.[15] 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

[11] 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.

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

[13] This can be computed $d_j = \sum_{j=1}^{N} a_{ij}$.

[14] Individual clustering coefficients can be computed $\text{clustering}_i = \frac{1}{d_i(d_i-1)} \sum_{j=1}^{N} \sum_{k=1}^{N} a_{ij} a_{jk} a_{ik}$.

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

$$\text{closeness}_i = \sum_j \frac{1}{distance(i,j)}.$$

average to the rest of the network, and hold network position in 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.[16]

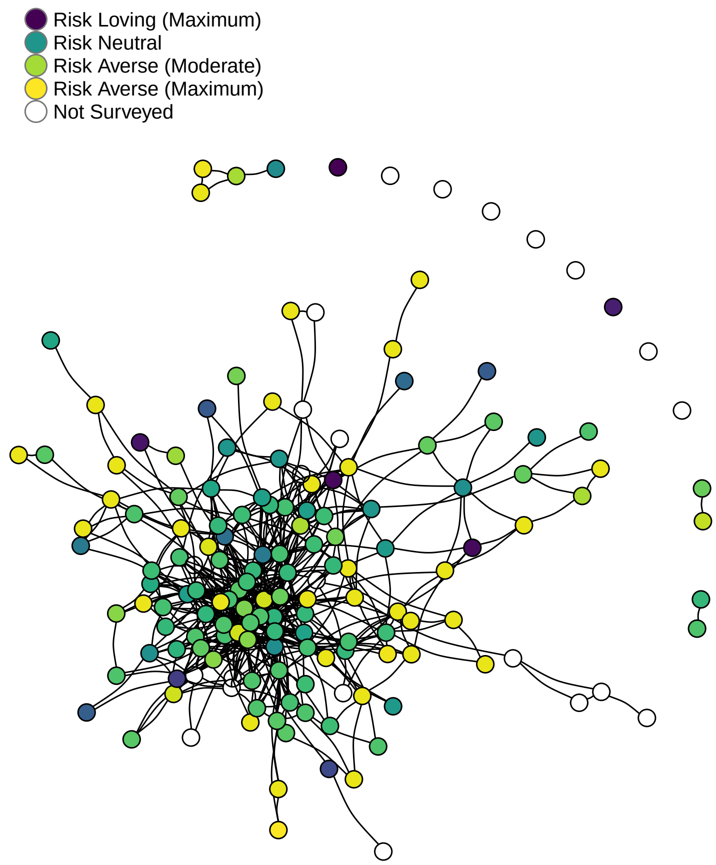


Figure 2: Risk sharing networks in village of Darmang with Constant Absolute Risk Aversion coefficeints indicated by color. For the distribution of risk preferences, see additionally Figure 7 which features a matching color coding.

[16]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.

3.2.3 Community Networks

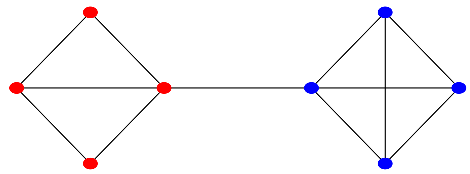
While canonical work on risk sharing modeled it at the village level (or some similar administrative unit), empirical work has shown that sharing is mediated by interpersonal relationships (Townsend, 1994; Fafchamps and Lund, 2003; De Weerdt and Dercon, 2006). Despite this, risk may often be shared at a wider radius than ones immediate friends and family. While in many contexts we can observe the radius via informal or quasi-formal risk pooling groups, I use community detection as a principled approach to capture the radius of risk sharing where such groups are not legible ((Newman, 2012; Putman, 2022)).[17] These communities consist of dense subnetworks with the larger risk sharing network. While the radius of risk sharing might be captured similarly by second order connections, these algorithms have the added advantage of partitioning the network into functional units. As explained within Putman (2022), these risk sharing communities are closely connected to kinds of risk sharing groups predicted by theory (Bloch et al., 2008; Ambrus et al., 2014).

I use the *Walktrap* algorithm, which uses random walks to determine the similarity between individuals and group similar individuals into communities (Pons and Latapy, 2005). The intuition is that these random walks will become trapped in tightly knit sections of the local network. Further discussion of this algorithm for risk sharing networks can be found in Putman (2022) and Appendix C.2. After I have assigned nodes to communities, I construct an additional risk sharing network using these community assignments, which I refer to as the community network. Assuming that effective risk pooling takes place at the community level, all nodes assigned to a particular 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} is an indicator variable equal to one if i and j are in the same community and zero if not. Like the adjacency matrix, C is symmetric. The differences in the bilateral risk sharing network and the community networks are depicted in Figure 3.

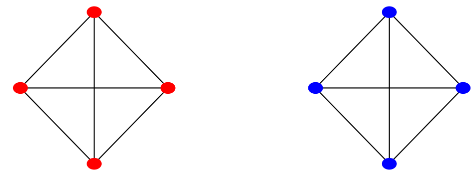
I assign individuals to risk pooling communities using walktrap community detection with walks of four steps applied to our risk sharing network.[18] For the resulting community detection see Figure 10.

[17]For example: 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).

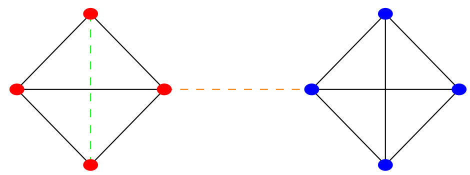
[18]Longer walks tend to result larger communities, whereas smaller walks result in smaller communities.



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



(b) Community Network: after detecting the communities, community co-membership links are formed within and removed across communities.



(c) The 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.

Figure 3: A stylized example of risk sharing networks, community networks and their differences.

4 Empirical Strategy

I will estimate a number of models of network formation to establish the degree of assorative matching in these risk sharing networks, including Subgraph Generation Models (SUGMs). However, 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. Additionally, they allow for traditional robustness checks on specification and in controlling for potential confounding variables.[19]

4.1 Dyadic Regression

4.1.1 Risk Sharing Networks

To establish the degree of assorative matching on risk preferences, I will start by estimating dyadic regressions, an econometric model of network formation. In these regressions, each pair of nodes is treated as an observation. In particular, the main effects are estimated as linear probability models. The most

[19]In particular, I note similarities and differences between these results and those found in Attanasio et al. (2012).

parsimonious model regresses risk sharing connections on differences in measured risk aversion,

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

where a_{ij} is an indicator for if i and j are connected in the risk sharing network, η_i is the risk aversion of individual i and ε_{ij} is the error term. Note that all variables enter symmetrically: $a_{ij} = a_{ji}$ (as the adjacency matrix A is symmetric) and explanatory variables are computed as to enter symmetrically (Fafchamps and Gubert, 2007). 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.

A second specification includes the sum of risk aversion η_i and η_j to control for the correlation between risk aversion and popularity, a difficult feature of the current cross-sectional setting. 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.[20] Whereas, in a panel setting, I might use a fixed effects approach to estimate degree heterogeneity, in this setting I rely on selection on observables for my main effect.[21]. Specifically, I control for the sum of risk aversion:

$$a_{ij} = \beta_0 + \beta_1 |\eta_i - \eta_j| + \beta_2(\eta_i + \eta_j) + \varepsilon_{ij} \tag{17}$$

A positive estimate of β_2 suggests that individuals who are more risk averse are less likely to link to each other. Furthermore, I take estimates of β_1 using this strategy as my preferred estimate of assorative matching from the dyadic regressions.

[20] 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. If those with lower risk aversion make riskier, higher reward decisions, this may be parlayed into income growth and higher SES in the long term (Elbers et al., 2007; Karlan et al., 2014). Third, though I have assumed constant absolute risk aversion, it is plausible that having better social standing could make a person less risk averse e.g., in a model of decreasing absolute risk aversion. 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.

[21] Notably, Graham (2017) introduces approach to control for degree heterogeneity in cross sectional settings which relies on combinations of data where fixed effect terms "net out" of the estimation, which I include as a robustness check.

4.1.2 Heterogeneity by Family Ties

A third specification examines kin ties as a predictor of risk sharing connections.

$$a_{ij} = \beta_0 + \beta_1|\eta_i - \eta_j| + \beta_3\text{Family}_{ij} + \varepsilon_{ij} \tag{18}$$

where family is an indictor variable equal to one if i and j report being kin and zero otherwise. 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 16 and 17.

$$a_{ij} = \beta_0 + \beta_1|\eta_i - \eta_j| + \beta_2(\eta_i + \eta_j) + \beta_3\text{Family}_{ij} + \varepsilon_{ij} \tag{19}$$

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

$$a_{ij} = \beta_0 + \beta_1|\eta_i - \eta_j| + \beta_2(\eta_i + \eta_j) + \beta_3\text{Family}_{ij} + \beta_4\text{Family}_{ij} \times |\eta_i - \eta_j| + \varepsilon_{ij} \tag{20}$$

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.

4.1.3 Community Network

I re-estimate the above dyadic regressions 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 $i \neq j$ are in the same detected community, and 0 otherwise.

4.1.4 Estimation and Standard Errors

As mentioned above, I estimate these dyadic regressions as linear probability models, though I estimate logistic regressions as a robustness check (see Tables 8 and 9 in Appendix C.3.2). Importantly, errors are non-independent in dyadic regressions. In particular, the residuals of dyads involving a particular node might be arbitrarily correlated. Formally, it may be the case that $Cov(\varepsilon_{ij}, \varepsilon_{lk}) \neq 0$ if $i = l$, $i = k$, $j = l$, or

$j = k$. To correct standard errors for this type of 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).

4.2 Subgraph Generation Models

4.2.1 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.[22] A *subgraph* (sometimes called an 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 central node connected to the two others), a pair and an isolate (two nodes connected and one unconnected), or an empty subgraph (three unconnected nodes). 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 line. Likewise, while a link is a subgraph of interest, two unconnected nodes is not.

I directly estimate the parameters using an algorithm given by Chandrasekhar and Lewis (2016) and Chandrasekhar and Jackson (2018).[23] 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. To estimate the true rate of subgraph generation, 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 (that is, one composed of a greater number of nodes). 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,

[22] 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 (Chandrasekhar and Jackson, 2018). To the contrary, empirical of risk sharing would expect links are dependent on each other, see for example Jackson et al. (2012).

[23] SUGMs can also be estimated using GMM.

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.[24]

4.2.2 Links and Isolates Subgraph Generation Model with Types

The SUGMs seek to understand how individuals of different risk preferences connect to each other. I estimate SUGMs with both links and isolates, differentiated by types, which I base on preferences. There are two models of interest: a baseline model a preference model. Details of the estimation of these models can be found in Appendix C.4.2.

I start with the baseline model. For various reasons, a small subset of individuals in the network did not participate in the survey module I use to recover risk preferences.[25] Additionally, those who are risk loving would not choose to join in a risk sharing arrangement. I term both those who were not surveyed and those who are risk loving as nuisance nodes. Therefore, to understand the baseline rate of subgraph generation among the risk aversion, I estimate a model with two types. I estimate five features: isolates of risk averse nodes, isolates of nuisance nodes, and links within nuisance nodes, links between risk averse and nuisance nodes.

The second model I refer to as the preference model. I estimate the full model with less risk averse, more risk averse, risk loving, and non-surveyed types for a total of four types. This includes isolates of each type, links within each type, and links between each pair of types for a total of 14 features.

4.2.3 Pooled Subgraph Generation Models

AS my data has four unrelated networks, I need to make choices as to how to handle these multiple networks in the SUGM. 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. To do so, I cannot 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

[24] If I to added 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.

[25] 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.

I need to collect counts of features and potential counts of features in all four villages before combining. Details of this modification can be found in Appendix C.4.2.

4.2.4 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 Preferences SUGM with the results of the Baseline 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 2 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[26], and using parameter estimates as stand-ins for their means, I can use an analytic expression to estimate their variance. See appendix C.4.3 for more.

5 Results

5.1 Dyadic Regression

5.1.1 Risk Sharing Network

Table 2 reports the results from estimating the dyadic regression specifications (i.e., equations 16, 17, 18, 19, and 20). 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 are computed using dyadic robust standard errors. To make results more interpretable, I transform risk aversions into z-scores before computing regressors, so β_1 estimates the effect of a one-standard deviation absolute difference in risk aversion.

Columns (2) and (5) present my preferred specifications. Across all specifications I see negative estimates for the effect of difference in absolute risk aversion on the likelihood of linking in the risk sharing

[26] See, for example: https://www.stat.cmu.edu/ hseltman/files/ratio.pdf.

Table 2: Dyadic Regression: Bilateral Risk Sharing Network

	Match between i and j in 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)
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 computed using dyadic robust standard errors. All specifications are dyadic linear probability models with matching in the risk sharing network as the dependent variable. η_i is risk aversion of individual i, so $|\eta_i - \eta_j|$ is the absolute difference of risk aversion while $\eta_i + \eta_j$ is the sum. Both absolute differences and sums of risk aversion are transformed into z-scores.

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

network. 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, proxying for degree with the sum of risk aversion in column (2) yields a negative and significant estimate (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 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 falls. 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 $\hat{\beta}_1 + \hat{\beta}_4 = -0.0351$, statistically significant at the 0.1% level ($\chi^2(1) = 13.68$). Interpreting the coefficient,

Table 3: Dyadic Regression: Community Network

	Match between i and j in Community Network				
	(1)	(2)	(3)	(4)	(5)
$\|\eta_i - \eta_j\|$	-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)
family$_{ij} \times \|\eta_i - \eta_j\|$					-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 computed using dyadic robust standard errors. All specifications are dyadic linear probability models with matching in the community network as the dependent variable. η_i is risk aversion of individual i, so $|\eta_i - \eta_j|$ is the absolute difference of risk aversion while $\eta_i + \eta_j$ is the sum. Both absolute differences and sums of risk aversion are transformed into z-scores.

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

between family members a one standard deviation difference in risk aversion reduces the probability of linkage by 3.51 percentage points.

5.1.2 Community Network

Table 3 reports the results from re-estimating equations with the community network as the outcome of interest. The estimates of β_1 are negative and small in magnitude. 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 ($\chi^2(1) = 1.36$). Hence, I fail provide evidence for assortative matching in the community network regressions.

5.1.3 Addressing Threats to Validity

Before moving on to the results of the Subgraph Generation Models–which echo the results presented above–it is useful to address threats to validity for the dyadic regression results presented here. Qualitatively, the pattern of results in Tables 2 and 3 are highly robust to controlling for demographic factors and network centrality. See Appendix C.3.1 for detailed results using this selection on observables approach for the linear probability model. That is, I find assortative matching on risk sharing when controlling for the sum of risk aversion, and this assortative matching attenuates in community networks. Likewise, results are robust to choice of specification. Appendix C.3.2 present results from dyadic logistic regression, which similarly echoes the those from the linear probability models.

To be sure I can justify using sum of risk aversion as an ad hoc control for popularity, I utilize a network formation model termed tetrad logit, which is designed for situations where concerns arise around heterogeneity in degree when estimating assorative matching (Graham, 2017). Intuitively, this method selects tetrads of nodes (sets of four nodes and their connections) to contribute to the estimate if the node fixed effects for degree drop out within that tetrad, thereby "netting out" heterogeneity in popularity. This allows for estimates of assorative matching unconfounded by popularity. I describe the tetrad logit estimator and present results in Appendix C.3.3. I estimate models for each village network which lead to three insights. First, results unconditional on the sum of risk aversion from tetrad logit are similar to those from other methods (e.g., logit) when conditioning on the sum of risk aversion. Second, after controlling for popularity, controlling for the sum of risk aversion does not substantially change estimates. Third, assorative matching also attenuates in community networks using this estimator. These results give me confidence that the sum of risk aversion is controlling for a nuisance correlation between risk aversion and popularity.

5.2 Subgraph Generation Models with Types

5.2.1 Risk Sharing Network

The SUGM results for the coefficients of interest are presented in Table 4. While these are abridged for clarity, full results of all SUGM models are available in Appendix C.4.4. Using the baseline model, I estimate that individuals who are risk averse tend to form links with 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 with each other at a rate of 9.28%, more than twice the rate in the risk sharing network.

Considering the coefficients of interest from the preferences model, I derive two main findings. First, I see further evidence of assortative matching on risk preference by less risk averse individuals. Less risk

Table 4: Links and Isolates Pooled Subgraph Generation Model: Coefficients of Interest and Coefficient Ratios.

	Risk Sharing Network		Community Network	
Model, Subgraph	Stat.	Std. Err.	Stat.	Std. Err.
Baseline SUGM Coef.				
Within: All Risk Averse	0.0404	0.0009	0.0928	0.0013
Preferences SUGM Coef.				
Within: Less risk averse	0.0561	0.0010	0.1189	0.0015
Within: More risk averse	0.0299	0.0008	0.0713	0.0012
Between: More, less risk averse	0.0360	0.0008	0.0876	0.0013
Ratio of Coefs: Preferences/Baseline				
Within: less risk averse	1.389	0.040	1.281	0.024
Within: more risk averse	0.740	0.026	0.768	0.017
Between: less, more risk averse	0.891	0.028	0.944	0.019

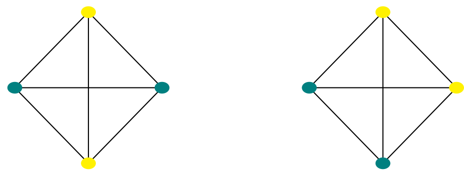
Sample size for features of interest is 49536 dyads. Models are abridged, focusing on coefficients and ratios of interest. For full results, Baseline SUGM coefficients are presented in Tables 14 and 15 and preference SUGM Coefficients are presented in Tables 16 and 17 Coefficient ratios are used to compare the two models, since higher average degree (as is present the community network) will result in higher coefficient estimates. SEs for coefficients are computed as shown in Appendix C.4.2 and SEs for ratios are computed as shown in Appendix C.4.3.

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

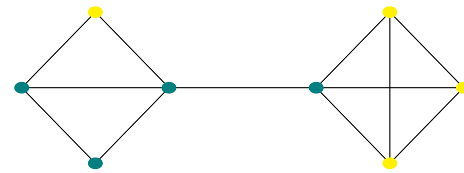
5.2.2 Community Network

The assortative matching in the community network mirrors the pattern in the risk sharing network (see Table 4). 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%).

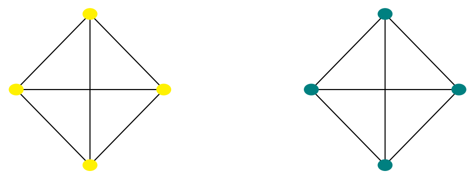
However, when making an apples to apples comparison between the degree of assortative matching in the risk sharing network and the degree in the community network, I see that the degree of assortative matching falls in the community network. Measuring the degree of assorative matching as the ratio of



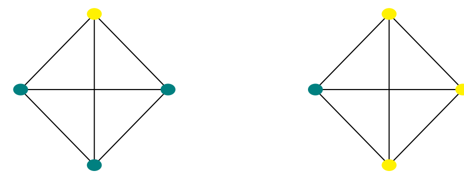
(a) No Assortative Matching: optimal composition of risk pooling communities. $\tilde{\beta}^{C}_{L,1,2} = 0.5$ and $p^U = 0.5$.



(b) Some assortative matching in a risk sharing network. $\tilde{\beta}^{C}_{L,1,2} = 0.3125$ and $p^U = 0.8061$.



(c) Complete Assortative Matching: a worst case composition of risk pooling communities. $\tilde{\beta}^{C}_{L,1,2} = 0$ and $p^U = 1$.



(d) Some assortative matching: a suboptimal composition of risk pooling communities. $\tilde{\beta}^{C}_{L,1,2} = 0.375$ and $p^U = 0.75$.

Figure 4: Stylized scenarios. Yellow is more risk averse, teal is less risk averse.

the rate of between links to the rate of links between all risk averse individuals, see Table 4. The ratio of within types for less risk averse is higher in the risk sharing network, whereas the ratio of between types is lower. Essentially, this indicates a reduced degree of assorative matching in the effective risk sharing communities.

6 Welfare Implications of Assortative Matching

6.1 Scenarios

What are the welfare implications of the degree of assortative matching? To quantify this effect, I compare among four scenarios. I list these scenarios here from high to low in terms of aggregate welfare:

(a) Optimal scenario: The planner's optimum with equal numbers of types. This scenario features no assortative matching.

(b) Community scenario: takes the degree of assortative matching implied by community network SUGM estimates. Features some assortative matching.

(c) Bilateral scenario: takes the degree of assortative matching implied by risk sharing network SUGM estimates. This features slightly more assortative matching than in the community scenario.

(d) Worst case scenario: complete assortative matching.

These scenarios are visualized in Figure 4.

6.2 Simulation Approach

To look at these counterfactual scenarios, I use a simulation approach. Before simulating, I remove all individuals who do not have preference data, or who are not risk averse and discard resulting "communities of one." Each simulation proceeds as follows:

1. Sort communities into two bins with roughly equal total population. The first bin will be majority type 1 and the second will be majority type 2[27]
2. Assign nodes of differing types to communities using a binomial process, varying the probability of success in that process according to what is implied by that scenario. A success assigns a majority type node to that community while a failure assigns a minority type node.
3. Compute the value function in units of Purchasing Power Parity (PPP) for each community and average welfare across communities in all four villages.

As noted in step 2 above, 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 SUGM coefficients using only the number of each type in the community. This is useful because it can give us an analytic expression for the average proportion of the majority type in each community as a function of the SUGM coefficients. By construction, the majority type will be type 1 in about half of the communities and type 2 in the other half.[28] Using simplifying assumptions (covered in detail in Appendix C.5) I am able to express the average proportion of the majority type, p^U ("p upper"):

$$p^U = 0.5 + 0.5 \times \sqrt{1 - \left(\frac{N-G}{N-1}\right)\left(\frac{\tilde{\beta}_{L,1,2}}{\tilde{\beta}_{ra}}\right)} \tag{21}$$

[27]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.

[28]I express this ratio as

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

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

Figure 4 visualizes this correspondence within each scenario in a stylized network. Once I obtain p^U for a scenario, it becomes the basis for a simulation of communities. I simulate community membership as a N_g (community size) draws from a binomial distribution with $\bar{p}^U$ with success being defined as a type 1 agent or a type 2 agent, respectively.

6.3 Simulation Results

I simulate community membership 50000 times, compute the value functions, and plot the results in Figure 5. The results are as follows:

(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 -136.76PPP

(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 -141.38PPP in this scenario.

(c) The bilateral 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 -142.13PPP 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 -156.43PPP in this scenario.

The average differences in scenarios are presented in Table 5. Due to relatively similar degrees of assortative matching in the bilateral and the community scenario as estimated by the SUGM, 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. These results are also influenced by the size of measured risk aversion, for which the upper bound binds. For more, Appendix C.5.4 discusses the impact of varying measured risk aversion on the welfare impact of assortative matching in theory.

7 Conclusion

7.1 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 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. 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

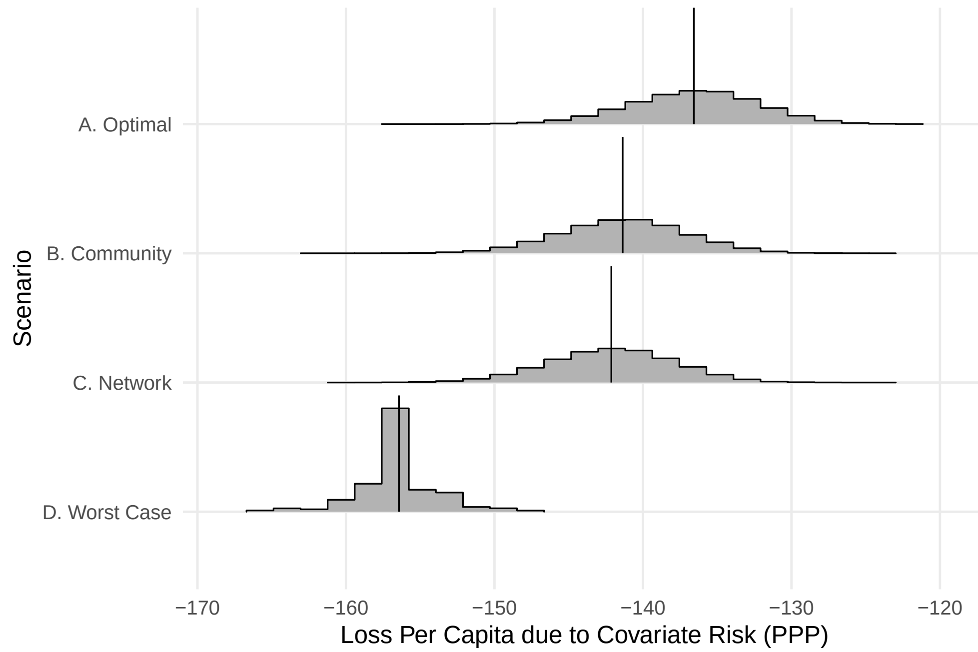


Figure 5: Histograms plots of welfare losses due to risk from 50000 simulations, scenario means are vertical black lines.

of types to communities.

7.2 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 in my side. 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.[29]

Second, measures of risk aversion are bounded by the approach to measurement. 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 theoretical model. In particular, the greater the degree of risk aversion, the greater the losses for a given level of assorative matching on

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

risk preferences. Figure 11 in the Appendix depicts this point. Based on this line of reasoning, it is very 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 may depend additionally the access and adoption of financial services.

7.3 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 theoretical models. For example, the theoretical model in 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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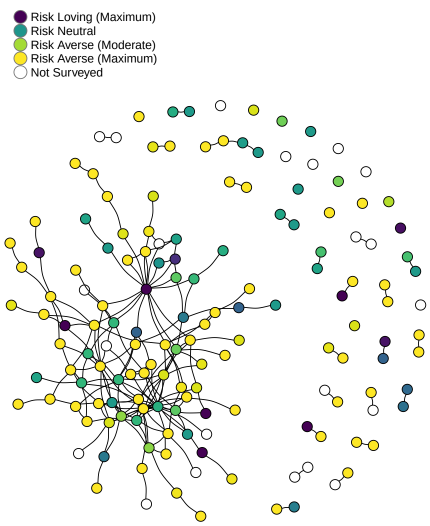
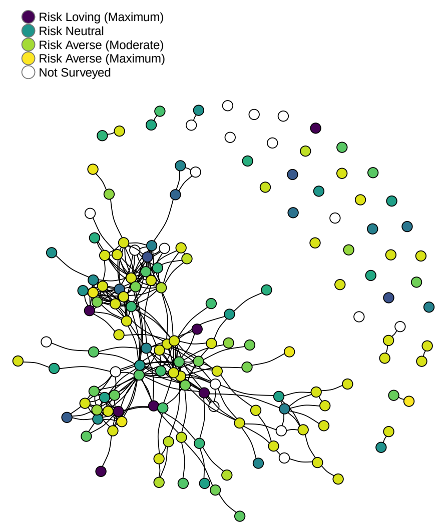
A Additional Figures



(a) Pokrom



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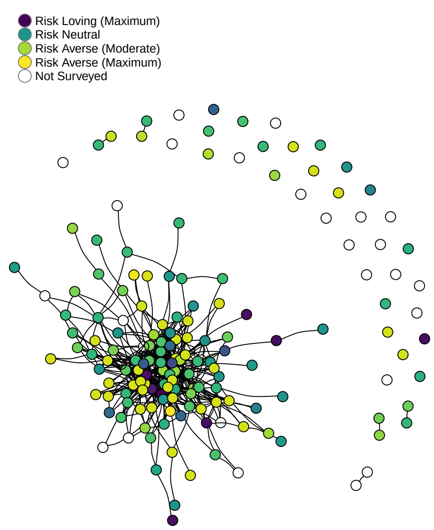


(c) Konkonuru

Figure 6: Risk Sharing Networks in Villages with Risk Aversion Indicated by Color

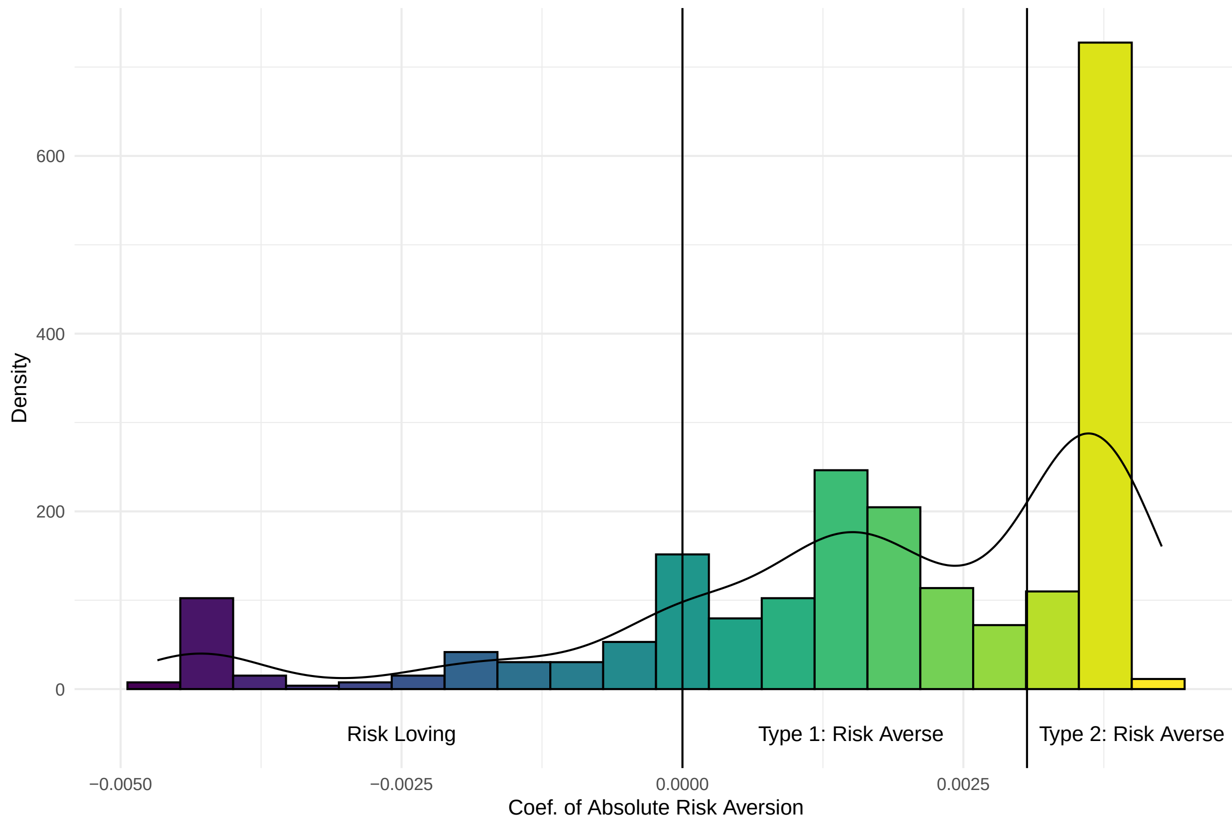


Figure 7: Histogram and distribution of risk preferences within the four villages. The histogram fill, which depicts the measured degree of risk aversion from the hypothetical gambles, is matched with Figures 2 and 6. Vertical lines indicate distinctions between types, which are annotated on the x-axis.

B Theoretical Appendix

B.1 Risk Sharing in Communities

B.1.1 Expected Utility

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

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

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:

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

So then I write expected utility

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

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

$$EU_0 = -\frac{\eta_{2i}}{2} \sigma_c^2.$$

B.1.2 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:

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

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

B.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:

$$\frac{\partial \mathcal{L}}{\partial \lambda_1} = 1 + bp = 0 \tag{22}$$
$$\frac{\partial \mathcal{L}}{\partial \lambda_2} = a + b(1-p) = 0 \tag{23}$$
$$\frac{\partial \mathcal{L}}{\partial \theta} = \frac{-\eta_1\theta\sigma_c^2}{p^2} + a_2\left(\frac{\eta_2(1-\theta)\sigma_c^2}{(1-p)^2}\right) \tag{24}$$
$$\frac{\partial \mathcal{L}}{\partial a} = \lambda_2 - \frac{\eta_2}{2}\left(\frac{1-\theta}{1-p}\right)^2\sigma_c^2 + \frac{\eta_2}{2}\sigma_c^2 = 0 \tag{25}$$
$$\frac{\partial \mathcal{L}}{\partial b} = p\lambda_1 + (1-p)\lambda_2 = 0 \tag{26}$$

Using FOC 22 I note that $b = -\frac{1}{p}$. Likewise, using FOC 23 I note that $a = \frac{1-p}{p}$. Rearranging FOC 25,

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

I rearrange FOC 26 and substitute in FOC 25:

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

Finally, I simplify FOC 24 to find θ:

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

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

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

so then

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

B.1.4 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,

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

B.1.5 Value Functions

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

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

Type 2:

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

B.2 Community Size and Composition

Optimal composition of communities occurs when the proportion of individuals within the community is equal to that in the village. As a demonstration is not an artifact of equal sized communities, in Figure 8, 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.

In addition, it is interesting to understand what proportion of covariate risk is shared in each community as a planner sorts types into two communities. Figure 9 demonstrates how the proportion of risk sharing in larger and smaller community vary by composition. As type 1 individuals move from the larger community to the smaller community, a greater proportion of covariate risk, encapsulated by θ is taken on by these individuals within the smaller community. This results in a risk management frontier which is bowed out. When more risk neutral agents are all in the larger or smaller community, they come close to taking on all of the covariate risk.

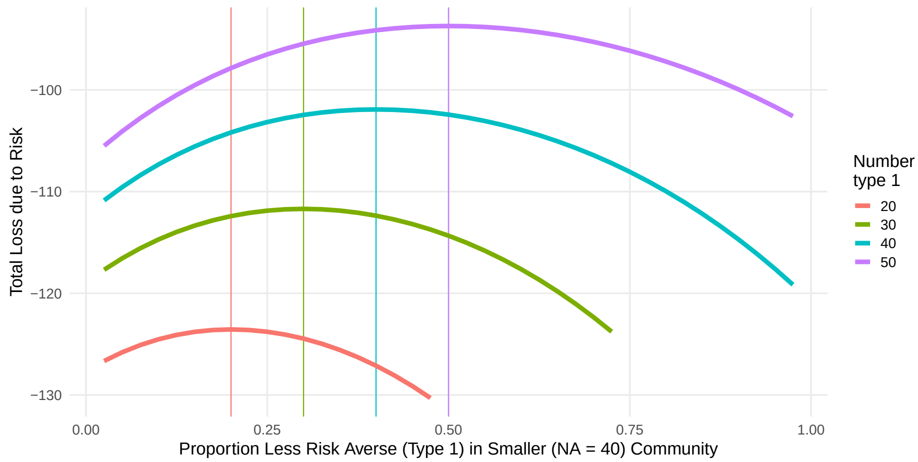


Figure 8: Optimal Allocation of Types Between Unequally Size Communities with varying numbers of Type 1 and Type 2 agents.

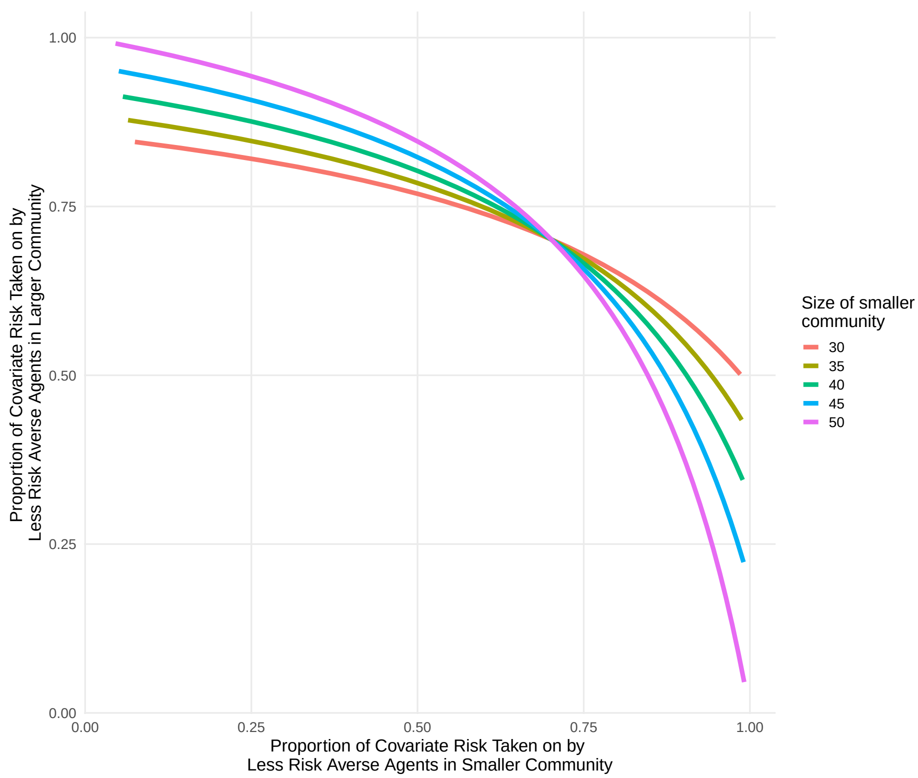


Figure 9: A Risk Management Frontier: Proportion of Covariate Risk Taken on by Less Risk Averse Agents in Communities. From top left to bottom right, type 1 agents move from larger community to smaller.

C Empirical Appendix

C.1 Measuring Risk Preferences

For each gamble, let Y_A be constant and let Y_B be normally distributed. For an agent with CARA preferences, I represent expected utility as a mean variance utility function (Sargent, 1987).

$$EU_i(Y) = E(Y) - \frac{\eta_i}{2}V(Y) \tag{27}$$

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.

C.2 Community Detection

C.2.1 Walktrap Algorithm

At a high level, the Walktrap algorithm proceeds as follows (Pons and Latapy, 2005):

1. To start, each node is assigned to its own community. Compute distances for all adjacent communities. See Appendix C.2.2 for a description of the computation of distances.
2. Merge the two adjacent communities with the smallest distance into one community.
3. Recompute the distances between communities.
4. Repeat steps 2 and 3 until all communities have been merged into one, recording the order of merges in a dendrogram (a hierarchical diagram documenting community merges).
5. Using the dendrogram, compare the modularity of all possible community assignments and choose the one with the highest modularity. See Appendix C.2.3. for computation of modularity.

C.2.2 Computing Distances using Random Walks

The Walktrap algorithm uses random walks to compute node similarity Pons and Latapy (2005). A random walk proceeds as follows: A random walker starts at node i and moves to an adjacent node with probability $1/d_i$ (where d_i is the degree of i). this process is repeated from the landing node, k, moving to an adjacent node with probability $1/d_k$, a total number of s times. If nodes are in the same community, random walks of length s from nodes i and j should often often land on the same nodes. Of course, nodes with higher degree will more often receive these walks, so the measure of distance takes account the degree of receivers.

$$r_{ij}(s) = \sqrt{\sum_{k=1}^{n} \frac{(P_{ik}^s - P_{jk}^s)^2}{d_k}}. \tag{28}$$

where P_{ik}^s is the probability that a walk starting at node i ends it's walk on node k. The distance overall can be thought of as the L^2 distance between P_{ik}^s and P_{jk}^s.

Building on this definition, they also define the distance between communities:

$$r_{C_1,C_2}(s) = \sqrt{\sum_{k=1}^{n} \frac{(P_{C_1,k}^s - P_{C_2,k}^s)^2}{d_k}}. \tag{29}$$

In this case, at the start of each random walk, the source within the community is drawn randomly and uniformly from members of that community:

$$P_{C,k}^s = \frac{1}{|C|} \sum_{i \in C} P_{ik}^s. \tag{30}$$

C.2.3 Modularity

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.

To compute modularity let d_i and d_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 $d_i d_j/(2m-1) \approx d_i d_j/2m$ ($2m$ 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:

$$A_{ij} - \frac{d_i d_j}{2m}$$

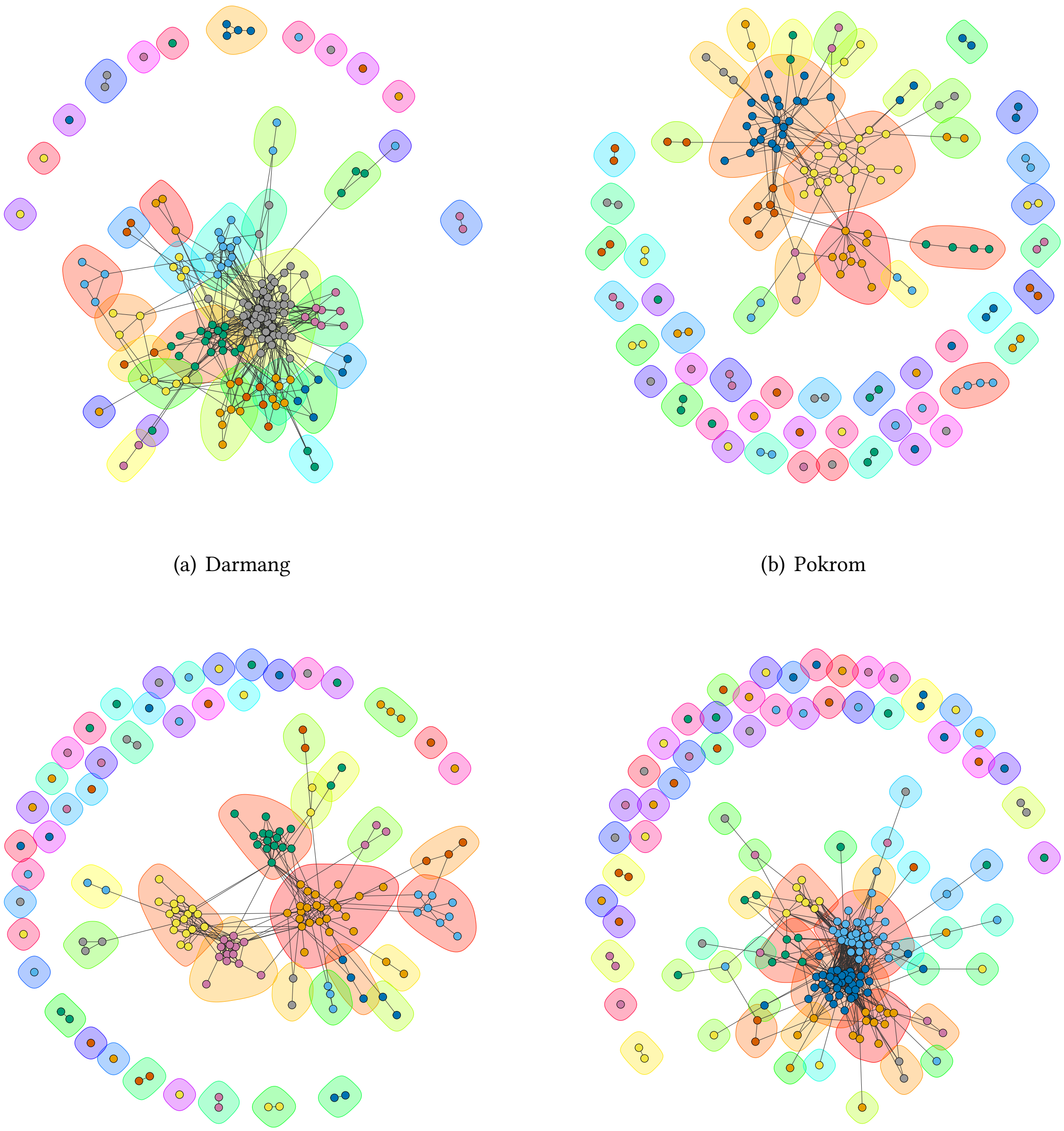
I can interpret this as connections over expected conditional on node pair degrees. Then, these values are weighted by if they reside in the same community, i.e., if $c_{ij} = 1$. Finally I aggregate to the graph level and normalize by twice the number of links present:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] c_{ij}$$

This serves as an easily computable and straightforward measure of the internal quality of communities (Newman, 2012).

C.2.4 Results of Community Detection

I detect communities using the *Walktrap* algorithm with random walks of length 4, which is standard for this algoithm. The results of the community detection algorithms are visualized in Figure 10.



(a) Darmang

(b) Pokrom

(c) Oboadaka

(d) Konkonuru

Figure 10: Risk sharing networks in villages with walktrap community detection assignment overlaid. Nodes are individuals and edges are links in the risk sharing network. Detected communities are represented by shaded regions and node colors.

C.3 Robustness Checks

C.3.1 Selection-on-Observables Results: Further Addressing Popularity and Homophily

Assortative matching on risk preferences could reflect 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). Tables 6 and 7 present results from the selection on observables approach. 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. Additionally, all regressions feature village fixed effects. 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 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 ($\chi^2(1) = 4.85$).

Table 6: 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)
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 7: Dyadic Regression: Community Network with Controls

	(1)	(2)	(3)	(4)	(5)
$\lvert\eta_i - \eta_j\rvert$	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)
family$_{ij} \times \lvert\eta_i - \eta_j\rvert$					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.

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

C.3.2 Logistic Regression Results

I estimate assortative matching using dyadic linear probability model because this allows me to utilize village fixed effects in my specifications. However, logistic regression is typically considered a more appropriate approach for binary dependent variables, including in network formation models. Therefore, to ensure my choice of specification does not influence the estimates of assortative matching, I replicate Tables 2 and 3 here using logistic regression. The results for logistic dyadic regression are estimated for the risk sharing network in Table 8 and the community network in 9. These replicate the pattern of results from the dyadic regressions in the main text. For the risk sharing network, we document assorative matching when using the sum of risk aversion to control for popularity. Results based on heterogeneity around family also replicate. Assortative matching on risk preferences is attenuated in the community network, even when the sum of risk aversion is controlled for.

Table 8: Dyadic Logistic Regression: Bilateral Risk Sharing Network

	(1)	(2)	(3)	(4)	(5)
$\lvert\eta_i - \eta_j\rvert$	-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)
family$_{ij}$ $\times$ $\lvert\eta_i - \eta_j\rvert$					-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 9: 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)
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

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

C.3.3 Tetrad Logit Results

As a robustness check on the role of degree heterogeneity, I estimate tetrad logit in each village (Graham, 2017).[30] Turning to the results, in Table 10 I focus on the estimates unconditional on the sum of risk aversion for each village. Two of these village cofficients are negative and of similar magnitude to the logit coefficient, while one is very close to zero, and one is 2.5-3 times as large as the logit coefficient. While three of these estimates are themselves insignificant, this is largely due to the loss in power from splitting my sample into four parts. In fact, the simple average of the village coefficients without controls is very similar to the logistic coefficient when controlling for the sum of risk aversion. Additionally, as presented in Table 11, the change in the estimate of the effect of the difference in risk aversion is not as pronounced in these estimates as it was in linear probability model or the logistic regression results presented earlier. The coefficients on the sum of risk aversion also fall in the tetrad logit specifications. This gives me confidence in the validity of my preferred specification as presented in the main text.

Interestingly, when this same back of the envelope calculation is done for the community tetrad logit results, I also find similar results to the logistic regression results. These can be found, by village, in Tables 12 and 13. This is consistent with a situation where measured assorative matching in the community network does not suffer from degree heterogeneity as a confounder in the same way that the risk sharing results do. As before, this represents an attenuation of assorative matching in communities relative to risk sharing networks.[31]

Table 10: Tetrad Logit with Risk Sharing Network: Unconditional Estimates

	Village				Simple Average
	Darmang (1)	Pokrom (2)	Oboadaka (3)	Konkonuru (4)	$=\frac{(1)+(2)+(3)+(4)}{4}$
$\lvert\eta_i - \eta_j\rvert$	-0.307	0.002	-0.094	-0.098	-0.124
	(0.058)	(0.052)	(0.051)	(0.067)	
Fraction Tetrads Used	0.074	0.035	0.045	0.076	

[30] It is theoretically possible to build an estimate from multiple villages by brute force, a back of the envelope check indicates to me that I do not have the computing resources to do so as my disposal. This might be avoided with greater understanding of the function that indexes tetrads, using this same function and adjusting the inputs to feed in the dyadic and tetrad mappings within villages.

[31] This fact may be useful for future empirical work on network formation. In particular, since community detection can construct communities of varying size, walktrap communities with short path lengths might in fact serve as useful in estimating assortative matching in practice.

Table 11: Tetrad Logit with Risk Sharing Network: Conditional Estimates

	Village				Simple Average
	Darmang (1)	Pokrom (2)	Oboadaka (3)	Konkonuru (4)	$=\frac{(1)+(2)+(3)+(4)}{4}$
$\lvert\eta_i - \eta_j\rvert$	-0.319	-0.063	-0.109	-0.119	-0.153
	(0.060)	(0.051)	(0.061)	(0.047)	
$\eta_i + \eta_j$	-0.050	-0.191	-0.069	-0.093	-0.040
	(0.065)	(0.108)	(0.076)	(0.071)	
Fraction Tetrads Used	0.074	0.035	0.045	0.076	

Table 12: Tetrad Logit with Community Network: Unconditional Estimates

	Village				Simple Average
	Darmang (1)	Pokrom (2)	Oboadaka (3)	Konkonuru (4)	$=\frac{(1)+(2)+(3)+(4)}{4}$
$\lvert\eta_i - \eta_j\rvert$	-0.214	-0.227	0.001	0.064	-0.094
	(0.060)	(0.111)	(0.073)	(0.068)	
Fraction Tetrads Used	0.074	0.035	0.045	0.076	

Table 13: Tetrad Logit with Community Network: Conditional Estimates

	Village				Simple Average
	Darmang (1)	Pokrom (2)	Oboadaka (3)	Konkonuru (4)	$=\frac{(1)+(2)+(3)+(4)}{4}$
$\lvert\eta_i - \eta_j\rvert$	-0.223	-0.204	-0.016	0.076	-0.092
	(0.111)	(0.089)	(0.076)	(0.071)	
$\eta_i + \eta_j$	-0.167	0.119	-0.122	0.134	-0.009
	(0.185)	(0.124)	(0.129)	(0.106)	
Fraction Tetrads Used	0.074	0.035	0.045	0.076	

C.4 Subgraph Generation Models

C.4.1 Estimation

For each model I estimate $\tilde{\beta} = \left(\{\tilde{\beta}_{I,\ell}\}_{\forall\ell}, \{\tilde{\beta}_{L,\ell,\ell}\}_{\forall\ell}, \{\tilde{\beta}_{L,\ell,r}\}_{\forall\ell,\forall r}\right)$. $\tilde{\beta}_{I,\ell}$ is the coefficient for isolates of type ℓ, $\tilde{\beta}_{L,\ell,\ell}$ is the coefficient for within links of type ℓ, and $\tilde{\beta}_{L,\ell,r}$ is the coefficient for links between type ℓ and r.

Coefficients for isolates of type l, $\tilde{\beta}_{I,\ell}$ are estimated

$$\tilde{\beta}_{I,\ell} = \frac{\sum_{i=1}^{n} \mathbf{1}(deg(i) = 0 | l_i = \ell)}{n_\ell}, \tag{31}$$

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

$$\tilde{\beta}_{L,\ell,\ell} = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \times \mathbf{1}(l_i = \ell) \times \mathbf{1}(l_j = \ell)}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{1}(l_i = \ell) \times \mathbf{1}(l_j = \ell)}, \tag{32}$$

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

$$\tilde{\beta}_{L,l,r} = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \times (\mathbf{1}(\ell_i = l) \times \mathbf{1}(\ell_j = r) + \mathbf{1}(\ell_i = t) \times \mathbf{1}(\ell_j = l))}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{1}(\ell_i = l) \times \mathbf{1}(\ell_j = r) + \mathbf{1}(\ell_i = t) \times \mathbf{1}(\ell_j = l)}. \tag{33}$$

For simplicity from herein I index features with s. From proposition C.2 in Chandrasekhar and Jackson (2018) under some sparsity conditions[32], $\Sigma^{-1/2}(\tilde{\beta}_n - \beta_0^n) \rightarrow N(0, I)$ where β_0^n is the true rate of subgraph generation. For a feature ℓ, the variance of the feature is the entry on the diagonal:

$$\Sigma_{s,s} = \frac{\beta_{0,s}^n (1 - \beta_{0,s}^n)}{\kappa_s \binom{n}{m_s}} \tag{34}$$

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,

$$\tilde{\sigma}_{s,s} = \sqrt{\frac{\tilde{\beta}_s^n (1 - \tilde{\beta}_s^n)}{\kappa_s \binom{n}{m_s}}}. \tag{35}$$

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

C.4.2 Pooled Subgraph Generation Models

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 31, 32,

[32] 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.

and 33 above. I estimate the coefficient associated with some subgraph s

$$\tilde{\beta}_s = \frac{\sum_{v=1}^{4} \text{count}_{sv}}{\sum_{v=1}^{4} \text{potential}_{sv}} \tag{36}$$

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

$$\tilde{\sigma}_{s,s} = \sqrt{\frac{\tilde{\beta}_s(1-\tilde{\beta}_s)}{\kappa_s \times \sum_{v=1}^{4} \binom{n_v}{m_s}}}. \tag{37}$$

C.4.3 Approximation of Variance of Ratios

We 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, but are unknown. Therefore, it is conservative to estimate the variance of the ratio by assuming $Cov(\tilde{\beta}_{L,s}, \tilde{\beta}_{L,ra}) = 0$, since this term enters negatively. This assumption leaves us with the expression

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

for the variance of the ratios.

C.4.4 SUGM Results

Table 14: Baseline Pooled Subgraph Generation Model with Risk Sharing Network

Feature	Count	Potential	Sample Size	Coef.	Std. Err.
Isolates:					
Nuisance	49	178	631	0.2753	0.0178
Risk Averse	41	453	631	0.0905	0.0114
Within links:					
Nuisance	76	3888	49536	0.0195	0.0006
Risk Averse	1030	25472	49536	0.0404	0.0009
Between links:					
Risk Averse, Nuisance	502	20176	49536	0.0249	0.0007

Baseline Pooled SUGM using Risk Sharing Network with features including links and isolates by whether nodes are risk averse or are nuisances. Nuisance nodes are those who either have unmeasured risk aversion (i.e., were not surveyed), or who are risk loving, who I assume would not engage in risk sharing. Count is the number of subgraphs which actually display the feature, Potential is the total number that could, and sample Size is the sample size used to estimate the Standard Error.

Table 15: Baseline Pooled Subgraph Generation Model with Community Network

Feature	Count	Potential	Sample Size	Coef.	Std. Err.
Isolates:					
Nuisance	56	178	631	0.3146	0.0185
Risk averse	60	453	631	0.1325	0.0135
Within links:					
Nuisance	177	3888	49536	0.0455	0.0009
Risk averse	2365	25472	49536	0.0928	0.0013
Between links:					
Risk averse, nuisance	1311	20176	49536	0.065	0.0011

Baseline Pooled SUGM using Community Network with features including links and isolates by whether nodes are risk averse or are nuisances. Nuisance nodes are those who either have unmeasured risk aversion (i.e., were not surveyed), or who are risk loving, who I assume would not engage in risk sharing. Count is the number of subgraphs which actually display the feature, Potential is the total number that could, and sample Size is the sample size used to estimate the Standard Error.

Table 16: Preferences Pooled Subgraph Generation Model with Risk Sharing Network

Feature	Count	Potential	Sample 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
Not surveyed	36	96	631	0.375	0.0193
Risk loving	13	82	631	0.1585	0.0145
Within links:					
Less risk averse	421	7511	49536	0.0561	0.001
More risk averse	186	6223	49536	0.0299	0.0008
Not surveyed	20	1133	49536	0.0177	0.0006
Risk loving	33	814	49536	0.0405	0.0009
Between links:					
Less risk averse, more risk averse	423	11738	49536	0.036	0.0008
Less risk averse, not surveyed	132	5879	49536	0.0225	0.0007
Less risk averse, risk loving	163	4765	49536	0.0342	0.0008
More risk averse, not surveyed	66	5057	49536	0.0131	0.0005
More risk averse, risk loving	141	4475	49536	0.0315	0.0008
Risk loving, not surveyed	23	1941	49536	0.0118	0.0005

Preferences Pooled SUGM using Risk Sharing Network with features including links and isolates by whether nodes are less risk averse, more risk averse, are risk loving, or have unmeasured risk aversion (were not surveyed). Count is the number of subgraphs which actually display the feature, Potential is the total number that could, and sample Size is the sample size used to estimate the Standard Error.

Table 17: Preferences Pooled Subgraph Generation Model with Community Network

Feature	Count	Potential	Sample 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
Not surveyed	39	96	631	0.4062	0.0196
Risk loving	17	82	631	0.2073	0.0161
Within links:					
Less risk averse	893	7511	49536	0.1189	0.0015
More risk averse	444	6223	49536	0.0713	0.0012
Not surveyed	42	1133	49536	0.0371	0.0008
Risk loving	59	814	49536	0.0725	0.0012
Between links:					
Less risk averse, more risk averse	1028	11738	49536	0.0876	0.0013
Less risk averse, not surveyed	379	5879	49536	0.0645	0.0011
Less risk averse, risk loving	373	4765	49536	0.0783	0.0012
More risk averse, not surveyed	248	5057	49536	0.049	0.001
More risk averse, risk loving	311	4475	49536	0.0695	0.0011
risk loving, not surveyed	76	1941	49536	0.0392	0.0009

Preferences Pooled SUGM using the Community Network with features including links and isolates by whether nodes are less risk averse, more risk averse, are risk loving, or have unmeasured risk aversion (were not surveyed). Count is the number of subgraphs which actually display the feature, Potential is the total number that could, and sample Size is the sample size used to estimate the Standard Error.

C.5 Welfare Simulations

C.5.1 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

$$\left(\sum_{g=1}^{G} N_{1g}\right)\left(\sum_{g=1}^{G} N_{2g}\right) = N_1 N_2.$$

So then

$$\tilde{\beta}_{1,2} = \frac{\sum_{g=1}^{G} N_{1g}N_{2g}}{N_1 N_2}$$

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 $\tilde{\beta}_{1,2}$

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

C.5.2 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

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

C.5.3 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:

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

C.5.4 The Welfare Impact of Risk Preferences

I measure risk aversion using hypothetical gambles. Though these gambles return those who are more and less risk averse, it is likely that the relatively low stakes of the hypothetical may yield coefficients of risk aversion much lower than we might observe with a high stakes incentivized gamble. Moreover, if risk aversion is underestimated, then the welfare impact of risk sharing will also be underestimated. Even within the local range of risk aversion measured, we can see non-trivial differences in losses due to risk. For example, Figure 11 shows how losses due to observed assortative matching increase with risk aversion of more risk averse agents.

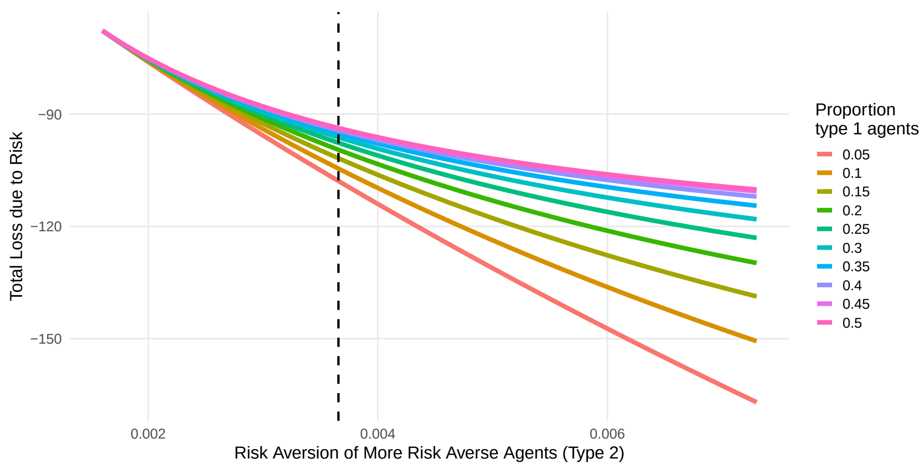


Figure 11: Greater risk aversion increases the welfare impact of assortative matching. As risk aversion increases villages with greater assorative matching will suffer more than those without. However, the delta between assortative is subject to diminishing marginal losses. The dashed vertical line indicates the measured degree of risk aversion among type 2 agents.