Sharing Covariate Risk in Networks: Theory and Evidence from Ghana

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Abstract

When risk preferences are heterogeneous, welfare can be improved by shifting covariate shocks from risk averse to risk tolerant people in exchange for a premium. However, this type of risk pooling depends on whether people prefer to share risk with others who have similar risk preferences. To investigate this question, I build a theoretical model of risk pooling with heterogeneous risk preferences. I use detailed data from Ghana to construct village risk sharing networks and community detection to construct community networks—which bound the scope of risk pooling. With econometric models of network formation, I estimate a preference to match on risk preferences in risk sharing networks. Within community networks, the magnitude of assortative matching falls considerably. I compare this allocation of types to three benchmarks, including an optimal and worst-case scenario, finding that the observed networks deviate only slightly from optimal networks for this form of risk pooling.

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

JEL Codes: D85, G52, L14, O12, O17, Z13

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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, the less risk averse agent takes the hit in a bad year; 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 local 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 in social and economic networks (McPherson et al., 2001). As has been documented experimentally, this pattern of positive *assortative matching* on risk preferences—or the

[1]With the adoption of mobile money and other digital payment systems in recent years, it is important to delineate this story of 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 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 a way for a more risk averse renter to pass risk to their less risk averse landlord (Stiglitz, 1974; Braverman and Stiglitz, 1986). Similarly, renters 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 50% of rental contracts (Goldstein and Udry, 2008).

tendency of those with similar risk preferences to be connected in networks—arises as a barrier to covariate risk sharing (Attanasio et al., 2012). Given the degree of assortative 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) I estimate the degree to which agents match with those who have similar risk preferences, and (ii) quantify the impacts to welfare from this aspect of network structure. To measure the degree of assortative 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 of 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 use two main measures of the risk pooling network. First, I measure the risk sharing network using the intersection of trust and gift networks. 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 assortative matching into concrete welfare estimates, I construct a theoretical model of optimal risk pooling in a village setting. In this model, I abstract away from the question of matching to focus on how a planner allocates individuals to subvillage groups. While idiosyncratic risk is assumed to be fully pooled at the group level, covariate risk is not. The social planner assigns individuals to two risk pooling groups according to their risk aversion in order 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.[3]

I use estimates from several econometric models of network formation to characterize assortative matching. These models use differences in risk preferences to explain connections in the risk sharing and community network. Dyadic regression, which treats dyads of individuals as the unit of study, serves as a reduced form approach to estimating assortative matching in risk preferences (Graham, 2020). Using this model, I estimate that individuals do prefer to assortatively

[3]Since I model high and low risk aversion individuals as types, I opt to describe optimal matching as no assortative matching as opposed to positive assortative matching, which tends to rely on the intensity of node level characteristics.

match on risk preferences in the risk sharing network. That is, they prefer to match with individuals who have a similar degree of risk aversion. While these results are conditional on controlling for the sum of risk aversion, doing so solves a subtle omitted variable problem by controlling for a correlation between popularity and risk aversion. Additionally, I find they are robust to alternative network formation models and modeling choices, including Subgraph Generation Models (SUGMs) (Chandrasekhar and Jackson, 2021).[4] Importantly, I structure the SUGMs to estimate assortative matching between types so that I can translate estimates of assortative matching to estimates of composition, as used within the theoretical model.

Exploring heterogeneity by family connections, I find stronger evidence of assortative matching within families, which may suggest a stronger preference to match when information is better. The SUGMs also 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.

As I increase the radius of risk sharing from the risk sharing network to the community network, assortative matching on risk preferences falls. In particular, using dyadic regression, I fail to find evidence for assortative matching.[5] 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 risk sharing relationships, and risk sharing networks among family feature less diverse preferences.

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) a 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 assortative 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

[4] In addition to estimating SUGMs, I estimate tetrad logit, a model designed to account for degree heterogeneity (Graham, 2017), where I find consistent results. The results are also robust to alternative specification choices particularly estimation as a logistic regression and controlling for a large set of dyadic characteristics. These controls include demographics, occupation, education, and (family) network centrality.

[5] As I do with the risk sharing network, I replicate these results using alternative specifications including LPM with controls, using dyadic logistic regression, and using tetrad logit.

networks already. I.e., if 0% is the worst case scenario, and 100% is the optimum, observed assortative matching in networks places 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 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 improving these tools.

This work contributes to the present 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 of the covariate risk in exchange for some increase in consumption over the long term. 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.[6]

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.[7] This reflects estimates from Attanasio et al. (2012) which find assortative matching in a risk pooling experiment done in the lab. Beyond replicating these results, the current work provides evidence of assortative matching on risk preferences in both real world risk sharing relationships and in a new country context, strengthening the external validity of this empirical result. Interestingly, these estimates are consistent with models of assortative matching on risk preferences in the presence of idiosyncratic risk sharing (Attanasio et al., 2012; Wang, 2015).

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 for risk sharing networks (Dizon et al., 2019; Dupas et al., 2019; Banerjee et al., 2022). By quantifying the importance of network structure, I reveal an important facet of the the net welfare effects of access to financial services. Second, some recent interventions seek to facilitate the expansion of interfirm networks, finding that these interven-

[6]More broadly, this work also contributes to the study of the kinds of risk insured by informal risk sharing networks as well as the constraints faced due to assortative matching: Gao and Moon (2016) and Jaramillo et al. (2015) study heterogeneity in risky endowments, while Xing (2020) studies heterogeneity in autocorrelation of (idiosyncratic) risk.

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

tions increase risk sharing transfers (Cai and Szeidl, 2018). This increase in the radius of risk sharing suggests decreased assortative matching from such interventions, which could have the added benefit of bolstering the conditions for covariate risk sharing. Third, climate change and growing interconnections in trade and financial 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.

2 Theoretical Model

In this section, I build a model that considers a risk-neutral planner seeking to construct two risk pooling communities in a village in order to maximize expected utility within risk averse members of the village. Here I leave aside community size and its impact on community composition and focus on optimal community composition itself. I consider community composition with regard to risk aversion, with relatively less and more risk averse individuals.[8] 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 planner's 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 covariate 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 the covariate risk. This covariate risk derives from both the average idiosyncratic shock—which in general is not zero—and a perfectly correlated covariate shock.[9] More risk averse agents are able to take on less of the covariate risk, shifting them onto 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.

[8]While, empirically, I also observe some risk loving individuals, I opt not to include them within the model. I explain my reasoning for this choice in Appendix A.1.1.

[9]This shock is perfectly correlated because I want to explore the role of assortative matching on risk preferences in the presence of covariate risk, as opposed to heterogeneity in income correlation between individuals.

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 is indexed by $\ell = 1, 2$. That is, $\eta_2 > \eta_1 > 0$. N_ℓ is the 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 shocks 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. $\lambda_{\ell i}$ regulates the recurring transfers from the more risk averse to the less risk averse. Thus, total transfers into the pot exceed the total transfer out: $-N_1\lambda_{1i} \leq N_2\lambda_{2i}$. Finally, due to the exponential utility function and normal distribution of shocks, I represent expected utility as a mean-variance decomposition (for details, see Appendix A.1.2):

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

2.1.2 Optimization Problem

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

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

$$\text{subject to} \qquad E(U_2(c_{2i}|\theta = p))) \leq E(U_2(c_{2i})) \tag{2}$$

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

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

$$0 \leq p\lambda_1 + (1-p)\lambda_2 \quad (5)$$

Constraint (2) is an incentive compatibility constraint: more risk averse agents cannot be 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, constraint (5) serves to ensure the feasibility of the recurring transfers (for details, see Appendix A.1.3).

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 A.1.4. The proportion of covariate risk shared will depend on the risk aversion and proportion of each type:

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

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 $\eta_2 > \eta_1$, $\theta^*(.) > p$ (for proof, see Appendix A.1.5). This means some degree of covariate risk is shifted to less risk averse individuals. Likewise, unless $\eta_1 = 0$ (I assume it does not) or $p = 1$, some risk is still taken on by the more risk averse. Furthermore, group composition matters for the degree of covariate 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:

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

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:

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

These solutions lead to the value functions (see Appendix A.1.6 for derivation):

$$V_1(p,\eta_1,\eta_2) = \frac{\eta_2}{2}\left(\frac{1-p}{p}\right)\left(1-\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2\right) \tag{9}$$
$$-\frac{\eta_1}{2}\left(\frac{\eta_2}{(1-p)\eta_1+p\eta_2}\right)^2\left(\frac{\sigma^2}{n}+\nu^2\right)$$
$$V_2(p,\eta_1,\eta_2) = -\frac{\eta_2}{2}\left(1+\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2\left(\left(\frac{\sigma^2}{n}+\nu^2\right)-1\right)\right). \tag{10}$$

2.2 The Planner's Problem

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

I state the planner's problem as follows:

$$\max_{N_{1A}} \quad N_{A1}V_1(p_{A1}) + N_{A2}V_2(p_{A1}) + N_{B1}V_1(p_{B1}) + N_{B1}V_2(p_{B1}) \tag{11}$$
$$\text{subject to} \quad N_\ell = N_{A\ell} + N_{B\ell}, \quad \ell = 1,2 \tag{12}$$
$$N_g = N_{g1} + N_{g2}, \quad g = A, B \tag{13}$$

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 it 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:

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

Solving this planner's 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 $\sigma_c^2 = 292.88^2$ (the square of the SE of net losses), $N = 100$, $N_1 = N_2 = 50$, 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 coefficients of

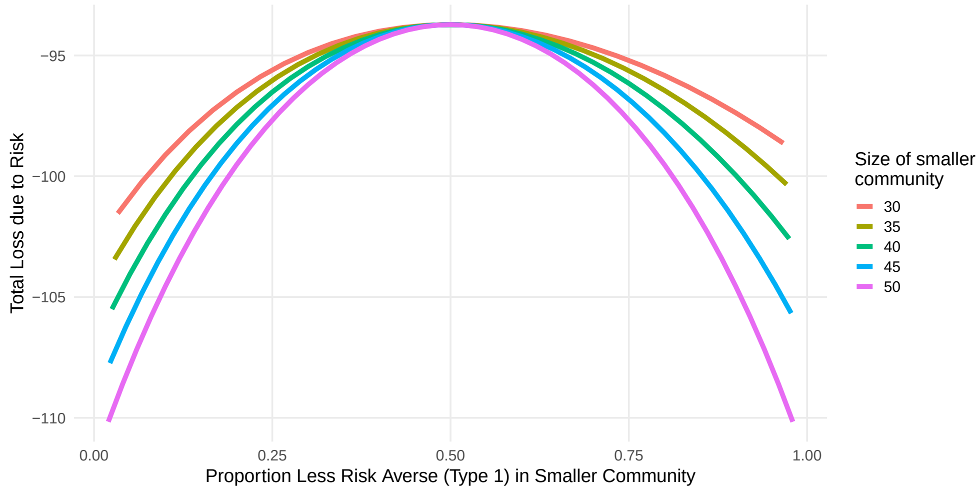


Figure 1: Optimal Allocation of Types Between Unequally Sized Communities

risk aversion and types).

Inspecting Figure 1, welfare is maximized when $p_{A1} = 0.5$, i.e., when diversity of types is maximized. Likewise, welfare is minimized as p_{A1} approaches 0 or 1, when diversity of types is minimized. Interestingly, unequally sized suboptimal communities improve over more equally sized suboptimal communities, holding p_{A1} equal. Also, 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, I plot the proportion of risk taken on by both groups as a risk pooling frontier in Figure 7. For a demonstration that this is not an artifact of equal numbers of type 1 and type 2 agents, see Appendix A.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).[10] Risk management within the villages includes substantial usage of these informal networks (Udry and Conley, 2005; Walker, 2011a). I utilize the 2009 network survey, which includes 631 individuals across the four villages. The data also features information about assets, income, and consumption shocks

[10]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 it is a strategy for smallholders to equip themselves to manage this risk through the use of local secondary markets.

(Barrett, 2009; Walker, 2011a).[11]

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. To construct risk pooling groups, I use community detection. The detected communities 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 the sure payment Y_A is increased. In the second menu, the sure payment is held fixed while the upside of the risky gamble is reduced. The third and fourth menus reflect the first and second set onto the losses domain.

To translate these hypothetical gambles into coefficients of risk aversion, I match assumptions to the theoretical model. First, I assume Y_B is normally distributed and second that individuals exhibit Constant Absolute Risk Aversion (CARA, or exponential preferences). These assumptions allow for a mean-variance representation of expected utility, which is crucial for the later welfare results (Sargent, 1987).[12] I compute $\hat{\eta}_i$ for each menu and individual using the sample analogue of the expression:

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

Finally, to combine these into measures of risk aversion, I average over menus. Precise details of how each coefficient is computed are available in Appendix B.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 9. Of those in the network who answered the elicitation module, I split these

[11] The survey instrument and further technical details can be found in Walker (2011b). A number of other empirical studies document features of the networks in this setting: Vanderpuye-Orgle and Barrett (2009) studies socially invisible members of the villages, and finds that risk pooling does not insure them as well as 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 in motivation (Nourani et al., 2019).

[12] In particular, it allows for the comparison of average incomes to the variance in income.

Table 1: Summary of Risk Sharing Network and Shocks by Risk Preferences

	More Risk Averse	Less Risk Averse	Risk Loving
Panel A: Network Statistics			
Average Degree	4.62	6.61	4.79
	(0.02)	(0.03)	(0.06)
Prop. Isolates	0.09	0.09	0.16
Average Clustering	0.25	0.23	0.23
	(0.00)	(0.00)	(0.00)
Average Betweenness	85.98	119.53	99.85
	(0.69)	(0.90)	(2.56)
Panel B: Income Shocks			
Average Net Losses	33.45	10.73	92.93
	(278.83)	(404.66)	(404.64)
Prop. Net Gain	0.34	0.34	0.27
Prop. Net Loss	0.28	0.19	0.28
N	236	217	96

For averages, standard errors are reported in parentheses below. 82 individuals who did not participate in the hypothetical gambles are excluded here. Risk loving have $\hat{\eta}_i \leq 0$, less risk averse (type 1) have $0 < \hat{\eta}_i < \eta_{\text{split}} \approx 0.003$, and more risk averse (type 2) have $\hat{\eta}_i \geq \eta_{\text{split}}$. Panel A: Degree is the number of other nodes directly connected to a node, $d_j = \sum_{j=1}^{N} a_{ij}$. Isolates are nodes with degree zero. Clustering is the average local clustering coefficient, which answers the question: for individual i connected to j and k, what proportion of the time are j and k also connected? Formally, $\text{clustering}_i = \frac{1}{d_i(d_i-1)} \sum_{j=1}^{N} \sum_{k=1}^{N} a_{ij}a_{jk}a_{ik}$. Betweenness centrality is the sum of shortest paths between other nodes in the network on which that node lies. Panel B: Shocks are unexpected losses or gains to income reported by the respondents summed up over individuals. I omit one outlying value for the tabulation of mean and variance, a net loss of about 48,000 Ghanaian Cedis reported by a type 2 (more risk averse) household.

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, $\eta_{split} \approx 0.003$.[13]

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

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

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.[14]

To construct the risk sharing network, I use the intersection of a gift network and a trust network to form a network of strong ties. In essence, connected dyads in this network include both one individual who recognized receiving a gift from the other and one individual who trusted the other to hold on to a valuable item (these might possibly be the same individual). This combination was chosen to include those who are trusted in the future after gifts have been exchanged in the past. However, I am cautious about gifts which are not reported due to issues of recall bias (Comola and Fafchamps, 2017). For this reason, I do not force the trust and gift networks to be individually reciprocal. Formally, $a_{ij} = \text{trust}_{ij} \times \text{gift}_{ij}$ where $\text{trust}_{ij} = 1(i \text{ trusts } j | j \text{ trusts } i)$ and $\text{gift}_{ij} = 1(i \text{ received from } j | j \text{ received from } i)$. Future work might use a more expansive network that intentionally includes weaker ties. With that said, the community networks presented in the next section extend the radius of risk sharing to others who are not strong ties. For more detail on network construction, see Appendix B.2.

Table 1 presents summary statistics about the risk sharing networks. When comparing less and more risk averse individuals there are differences in both degree and betweenness centrality. In particular, less risk averse individuals have higher degree—more risk sharing connections. Likewise, they have higher betweenness centrality—holding positions which bridge between other nodes—suggesting their importance in the routing of gifts and transactions through the network. This is both an unexpected and important feature of the data. Theory might predict that those with higher risk aversion would be central in risk sharing networks, reflecting a demand for insurance and issues of moral hazard (Jaramillo et al., 2015). Furthermore, heterogeneity in degree by underlying type can confound estimates of assortative matching (Graham, 2017). Despite these differences, it's interesting to note that the difference in clustering between less and more risk averse individuals would appear to be economically small.[15]

[14]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.

[15]Though it is beyond the scope 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.

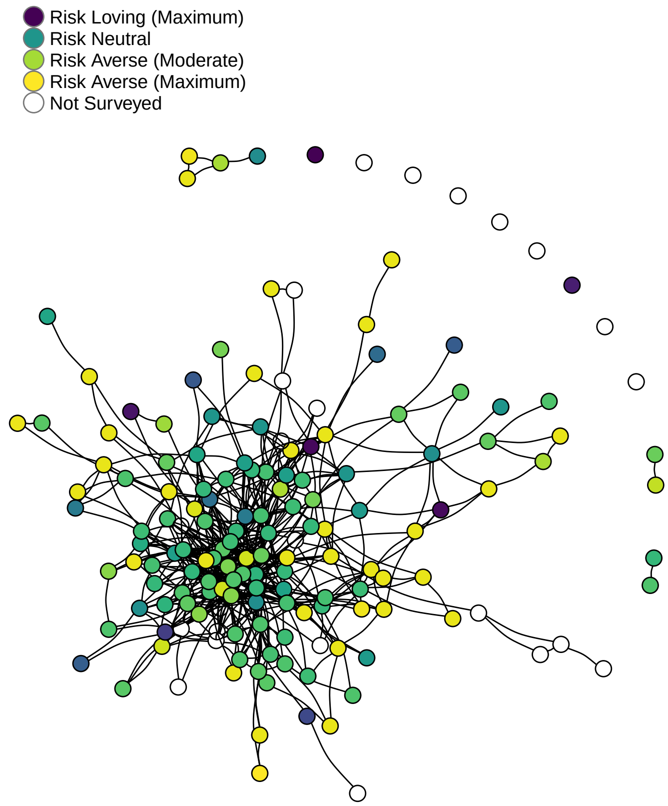


Figure 2: Risk sharing networks in village of Darmang with Constant Absolute Risk Aversion coefficients indicated by color. For the distribution of risk preferences, see additionally Figure 9 which features a matching color coding.

I also include summary statistics about income shocks faced by individuals in the sample in Table 1. While I caution against an entirely behavioral explanation for these shocks, some interesting patterns emerge. First, the risk averse (both type 1 and type 2) seem to work to limit their downside exposure relative to their upside exposure. Second, the variation in shocks among the less risk averse and risk loving is larger than those for the more risk averse. Despite this, those who are more risk averse face more downside risk than and have greater net losses those who are less risk averse, an important reminder that exposure to shocks depends on circumstances outside of risk preferences.

3.2.3 Community Detection and 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 one's immediate friends and family. In many contexts we can observe the radius of risk sharing via informal or quasi-formal risk pooling groups.[16] To match our empirical work to the theoretical model, it is handy to have such subvillage groups. However, in this context, such groups are not legible. Community detection has recently emerged to understand network structure on a meso to macro scale (Newman, 2012). Following Putman (2022), I use community detection to break up village networks into meso-level risk pooling communities.

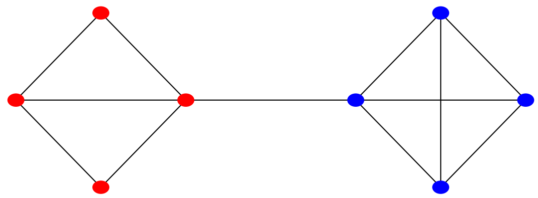
Community detection aims to assign nodes to modular communities. In our case, a good community assignment is one where most risk sharing connections fall within the community with only a few of the connections fall between communities. These risk sharing communities relate closely to partitions of networks within which risk would be theoretically completely shared and also explain behavior in a risk pooling experiment (Ambrus et al., 2014; Putman, 2022). Moreover, to the degree quasi-formal groups depend on group level rules (e.g. around repayment), they may have a more interchangeable structure than personal relationships. This is also reflected in the modular nature of the communities produced by these algorithms. Community detection algorithms partition the network into non-overlapping groups of individuals, in contrast to the overlapping networks of informal relationships.

My approach to uncovering communities is based on random walks through the network: A random walker moves from node-to-node in the network by way of edges, randomly selecting the next node it visits among those in the network neighborhood. In particular, I use the *Walktrap* algorithm, which uses these random walks to determine the similarity between nodes by the destinations of random walkers originating at that node (Pons and Latapy, 2005). The intuition is that these random walks will become trapped in tightly knit sections of the local network, meaning the algorithm will see nodes in tightly knit sections of the network as interchangeable and therefore group them together. In the world of risk sharing, this interchangeability of nodes is related to an interchangeability of risk sharing partners in the local network. Further discussion of this algorithm for risk sharing networks can be found in Appendix B.3.

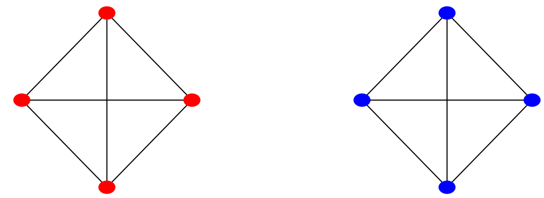
I assign individuals to risk pooling communities using Walktrap community detection on the risk sharing network with walks of four steps.[17] For a visualization of the resulting community

[16] Examples include mutual fire insurance in Andorra (Cabrales et al., 2003) and funeral societies in Ethiopia and Tanzania (Dercon et al., 2006).

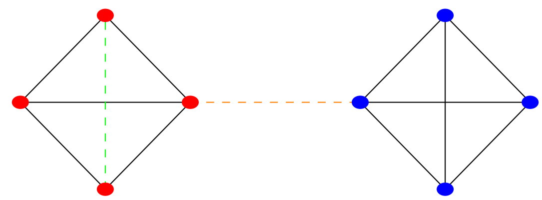
[17] Longer walks tend to result in larger communities relative to shorter walks. I opt for the default for four steps.



(a) A stylized risk sharing network with (latent to the econometrician) communities denoted by red and blue.



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



(c) The difference in networks: community network less the risk sharing network where green is added and 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.

detection, see Figure 11. 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. Since I assume no risk sharing takes place between communities, in this network no links occur between communities.[18] I represent the community graph using an adjacency matrix C where c_{ij} is an indicator variable for if i and j are in the same community. Like the adjacency matrix, C is symmetric. The difference in construction of the bilateral risk sharing network and the community network is depicted in Figure 3.

4 Empirical Strategy

In this section I describe the two main econometric models of network formation I use to estimate assortative matching on risk preferences. Each serves a different purpose within the paper. First, dyadic regression serves as a reduced form approach to describe assortative matching in the data. Its inclusion is beneficial as it allows for familiar exposition and interpretation as well as lending itself more easily to tests of robustness and comparison with past literature.[19] Second, SUGMs

[18] The theoretical results in Ambrus et al. (2014) suggest we would expect non-zero but small amounts of risk sharing between islands—which might tend to form *ex post* within *ex ante* communities. Likewise, the empirical results in Putman (2022) suggest very little risk sharing across communities.

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

serve to estimate assortative matching on risk preferences in a way that can be translated into the composition of risk sharing groups as is specified in the theoretical model. The estimates of these models will serve to inform the welfare results presented in Section 6.

4.1 Dyadic Regression

4.1.1 Risk Sharing Networks

To establish the degree of assortative 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. The most parsimonious model regresses risk sharing connections on differences in measured risk aversion,

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

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). A negative estimate of 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 account for degree heterogeneity, in this setting I rely on selection-on-

[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.

observables.[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 assortative matching from the dyadic regressions.

4.1.2 Heterogeneity by Family Ties

I examine how assortative matching varies by family ties. Family is interesting because it serves as a longstanding relationship. This means there may be a higher propensity to link overall, but also more information about potential risk sharing partners. We document the former in our third specification:

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

where family is an indicator variable equal to one if i and j report being kin. A positive estimate of β_3 suggests that family are more likely to be connected within the risk sharing network. A fourth specification combines specifications (16) and (17) to add the *ad hoc* control.

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

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

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

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. This might suggest greater information about others' preferences driving matching, as in Attanasio et al. (2012).

4.1.3 Community Network

It is also interesting to see how assortative matching changes as we relax the radius of risk sharing. While we do not have formal or quasi-formal risk sharing groups in this context sharing may take

[21] Notably, Graham (2017) introduces an 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.

place in a larger group context as it does in the theoretical model. I use detected communities to identify likely sharing partners who might lie beyond the immediate network neighborhood (Putman, 2022). 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.

The estimates of these models do not have as simple an interpretation as those for the risk sharing network. If we treat detected communities as informal risk sharing groups (legible to participants, but not to the econometrician), such a specification might accord with a coalition formation game with simultaneous announcement like those in Hart and Kurz (1983).[22] The dyadic regression coefficients on the difference in risk aversion can be interpreted within this framework as measures of assortative matching in the community network. After the groups have been formed, these partners might be interchangeable for the purposes of idiosyncratic risk sharing, and interchangeable conditional on risk preference for covariate risk sharing (similar to the theoretical model).[23]

4.1.4 Estimation and Standard Errors

I estimate these dyadic regressions as linear probability models, though I estimate logistic regressions as a robustness check (see Tables 9 and 10 in Appendix B.6.2). Importantly, errors are non-independent in dyadic regressions. In particular, the residuals of dyads involving a particular node might be arbitrarily correlated.[24] To correct standard errors for this type of non-independence, I use dyadic robust standard errors (Fafchamps and Gubert, 2007; Cameron and Miller, 2014; 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

[22] These models are not unlike those of pairwise stability found in Jackson and Wolinsky (1996). For example, in one game, to form a coalition, all members of the coalition must announce the same list of names, meaning they can exclude players by not including them in their list.

[23] There is more than one way to think about these estimates. In particular, we could think of these as a mix of chosen and incidental (but nonetheless relevant) effective risk sharing partners, an interpretation closer to Ambrus et al. (2014). For example, such incidental partners may be due to trusted community members (e.g., elders) who coordinate risk sharing within their area of the local network. In such a case the parameters of the community specifications would not be related to preferences for assortative matching.

[24] Formally, it may be the case that $Cov(\varepsilon_{ij}, \varepsilon_{lk}) \neq 0$ if $i = l$, $i = k$, $j = l$, or $j = k$.

subgraphs.[25] 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 a three node example, this means I leave aside pairs, isolates, 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.

4.2.2 Links and Isolates Subgraph Generation Model with Risk Preference Types

Like dyadic regression, SUGMs are estimated to understand how individuals of different risk preferences connect to each other. However, for these estimates I build the SUGMs to estimate the affinity within and between risk preference types. This allows me to recover community composition in terms of risk preferences in order to assess the welfare implications of assortative matching.[26] I estimate SUGMs with both links and isolates, differentiated by types, which I base on risk preferences. There are two models of interest: a baseline model and a preference model. 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.[27] Additionally, in the model, I study risk sharing among only those who are risk averse. I term both those who were not surveyed and those who have risk loving preferences as nuisance nodes. Therefore, to understand the baseline rate of subgraph generation among the risk averse, I estimate a model with two types. I estimate coefficients for five features: isolates of risk averse nodes, isolates of nuisance nodes, links within nuisance nodes, and links between risk averse and nuisance nodes. I refer to the second model 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.

I directly estimate the parameters using an algorithm given by Chandrasekhar and Lewis (2016) and Chandrasekhar and Jackson (2021). Estimating a SUGM directly is essentially estimat-

[25]While Exponential Random Graph Models have a similar motivation, they do not succeed at reconstructing graphs with any success. They depend on an assumption of independence of links. If this independence does not hold they are not consistent (Chandrasekhar and Jackson, 2021). To the contrary, many studies of risk sharing would expect links are dependent on each other. See for example Jackson et al. (2012).

[26]In the case of the community networks, I am actually recovering my estimate of assortative matching on risk preferences *from* the composition of communities. In contract, in the risk sharing network it comes from the assortative matching measure itself. This is because of the assumptions used in building the community network. To better understand this point, it is helpful to relate the SUGM to a Stochastic Block Model, as I do in Appendix B.4.4.

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

ing 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 the 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 the same size, order is arbitrary, but must exclude occurrences of this subgraph incidentally generated by other subgraphs which are further along in the order. For example, for a SUGM featuring links and triangles, I order links first, triangles second, etc. While counting links and potential links, I neglect pairs of nodes ij if jk and ik are in the graph.[28] More estimation details can be found in Appendix B.4.2.

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 (2021), 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, 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 B.4.2.

4.2.4 Differences in Assortative Matching

These SUGM estimates give me a way to test for assortative matching between risk sharing networks and community networks. However, 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 the ratio of Preferences SUGM coefficients to Baseline SUGM coefficients. I focus on the coefficients for within links for type 1 agents, within links for type 2 agents, and links between type 1 and 2 agents. For all three, I divide by the coefficient on links within any risk averse agents from the baseline model. This yields an excess affinity for connections among these dyads. Doing this for both the community coefficients and the risk sharing network coefficients, I can

[28] If I 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.

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$_{ij}$ × $\lvert\eta_i - \eta_j\rvert$					-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 are reported in parentheses and are 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

compare between the models. See appendix B.4.3 for details, including a conservative analytic approximation of standard errors.

5 Results

5.1 Dyadic Regression

5.1.1 Risk Sharing Network

Table 2 reports the results from estimating the dyadic regression specifications. I include village level fixed effects in all dyad regression specifications, though this does not affect the magnitudes estimated. Reported t-statistics are computed using dyadic robust standard errors. To make results more interpretable, I transform risk preferences 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 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), which I interpret as evidence of assortative matching on risk preferences. In particular, I estimate a one standard deviation difference in risk aversion leads a 2.16 percentage point reduction in the probability of connection.

As in other contexts, family connections are a strong determinant of co-participation in the risk sharing network. Across specifications (3), (4), and (5), having a family connection is positively associated with connection 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 than 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, a one standard deviation difference in risk aversion reduces the probability of linkage by 3.51 percentage points between family members. This might suggest stronger assortative matching when more information about risk preferences in available.

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 standard significance levels. Hence, I fail to find evidence for assortative matching in the community network regressions. Heterogeneity by family connections may provide some clues as to the differences. In particular, in column (5), $\beta_1 + \beta_2 = -0.012$ is not significantly different than zero ($\chi^2(1) = 1.36$). This suggests individuals are less able to be selective in their partnerships in the community network than in the risk sharing network.

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. That is, I find assortative matching on risk prefer-

Table 3: Dyadic Regression: Community Network

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

t statistics are reported in parentheses and are 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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ences when controlling for the sum of risk aversions, and this assortative matching attenuates in community networks. See Appendix B.6.1 for detailed results using this selection-on-observables approach for the linear probability model. Likewise, results are robust to choice of specification. Appendix B.6.2 presents results from dyadic logistic regression, which similarly echo 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 to account for correlations between heterogeneity in degree and type when estimating assortative matching (Graham, 2017). Intuitively, this method selects tetrads of nodes (sets of four nodes and their connections) which contribute to the estimate only if the node fixed effects for degree “drop out” within that tetrad, thereby “netting out” heterogeneity in popularity. This allows for estimates of assortative matching unconfounded by popularity. 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 accounting for popularity with tetrad logit, controlling for the sum of risk aversion does not substantially change estimates. Third, assortative matching also attenuates in community

Table 4: Links and Isolates Pooled Subgraph Generation Model: Coefficients of Interest from Baseline and Preferences Models 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: Pref./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

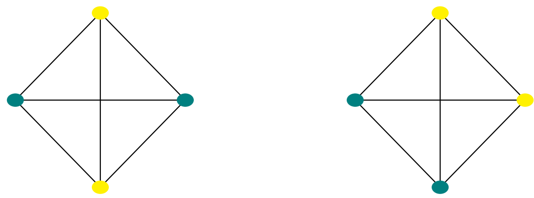
Sample size for features of interest is 49536 dyads. Models are abridged, focusing on coefficients and ratios of interest. For full results, Baseline SUGM coefficients are presented in Tables 13 and 14 and preference SUGM Coefficients are presented in Tables 15 and 16 Coefficient ratios are used to compare 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 B.4.2 and SEs for ratios are computed as shown in Appendix B.4.3.

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. I describe the tetrad logit estimator in greater detail and present results in Appendix B.6.3.

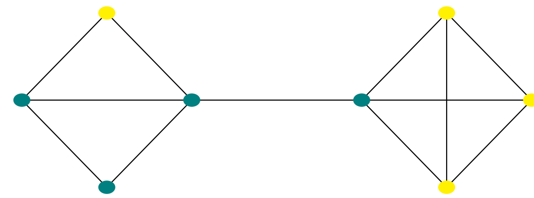
5.2 Subgraph Generation Models with Types

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 B.6.4. 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.

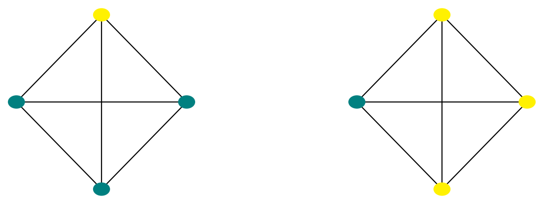
Considering the coefficients of interest from the preferences model, I derive two main findings. First, I see further evidence of assortative matching on risk preference by less risk averse individuals. Less risk averse agents form within-type links at a rate of 5.61% (compared to the base rate of 4.04%). Second, I do not see the same kind of assortative matching when looking at more risk averse 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 indi-



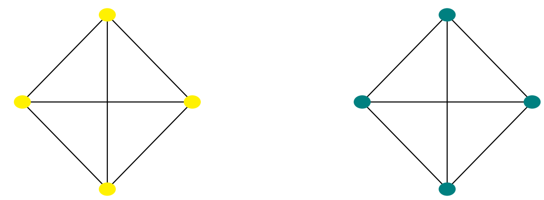
(a) No Assortative Matching: optimal composition of risk pooling communities. $\tilde{\beta}^C_{L,1,2} = 0.5$ and $p^U = 0.5$.



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



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



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

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

viduals form links between type (3.60%). In this way, less risk averse individuals drive assortative matching. In contrast, more risk averse types are more likely to form between links than within links.

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%).

The degree of assortative matching falls in the community network *vis a vis* the risk sharing network when we correct for the average number of links between individuals in the network. Restults measuring the degree of assortative matching as the ratio of the rate of between links to the rate of links between all risk averse individuals are also presented in Table 4. The ratio of within types for less risk averse individuals is higher in the risk sharing network, whereas the ratio of between types is lower. Essentially, this indicates a reduced degree of assortative matching in the effective risk sharing communities.

6 Welfare Implications of Assortative Matching

What are the welfare implications of the degree of assortative matching? To quantify this effect, I compare among four scenarios. I list these scenarios, which are visualized in Figure 4, 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.

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 of 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. Using simplifying assumptions (covered in detail in Appendix B.5), I am able to express the average proportion of the majority type, p^U ("p upper"):

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

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

To examine these counterfactual scenarios, I use a simulation approach. Each simulation proceeds as follows: first, I sort detected communities into two equally sized groups. The first of these is majority type 1 and the second is majority type 2. Second, I randomly assign individuals to communities using a binomial process, varying the probability of assignment by scenario. Specifically, I simulate community membership as N_g (community size) draws from a binomial distribution with $\bar{p}^U$ probability of success—success being defined as a type 1 agent or a type 2 agent, depending on which should be the majority type. Third, I compute the value functions for these random assignments using the derived value functions. For details of the simulations, see Appendix B.5.

I simulate community membership $50,000$ 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 is -136.76PPP

Table 5: Differences in Average Losses from Risk per Capita.

	...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

Results are averages from 50,000 simulation draws. Each entry in the table is the average per capita welfare from the scenario in the column less the average per capita welfare in the scenario in the row. Differences are in PPP Dollars.

(b) The community scenario has some assortative matching, as $R_{1,2} = 0.944$. I compute $p^U = 0.754$. The average loss due to risk is -141.38PPP.

(c) The bilateral scenario has slightly more assortative matching, as $R_{1,2} = 0.944$. I compute $p^U = 0.774$. 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.

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 be 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 the measured coefficients of risk aversion, for which the upper bound binds. For more, Appendix A.3 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 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 agents who have risk preferences unlike their own. 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 roughly the same proportion of more and less risk averse types as the village. This 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 is 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 radius of risk pooling, I see a reduction in assortative matching. While estimates vary, the magnitude of assortative matching falls in the community network.

Taking seriously the theoretical model of covariate risk sharing, 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 when compared to the losses due to the relatively small size of risk pooling communities. I estimate that on average \$141.38 PPP is lost due to covariate risk relative to a case where this could be fully insured. The optimal scenario averts only \$19.66 PPP of these losses relative to the worst case scenario. Additionally, risk pooling networks are relatively close to optimal when community size is held constant. I estimate the optimal scenario would avert only \$4.60 PPP over the same period when compared to the actual distribution of types to communities.

7.2 Limitations

I face some limitations in the estimation of the network formation models and the welfare simulations. First, while 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 (particularly due to popularity), the reflection problem applies to network formation just as it does peer effects (Manski, 1993). Do people match with those who have similar risk preferences, do they have similar risk preferences because they match, or do they have similar risk preferences because they face similar environments? While the preferred interpretation of a model of network formation would be the former, other stories remain plausible.[29]

Second, coefficients of risk aversion are censored by the survey instrument. In this data, about 25% of individuals who are surveyed about their preferences choose the most risk averse options

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

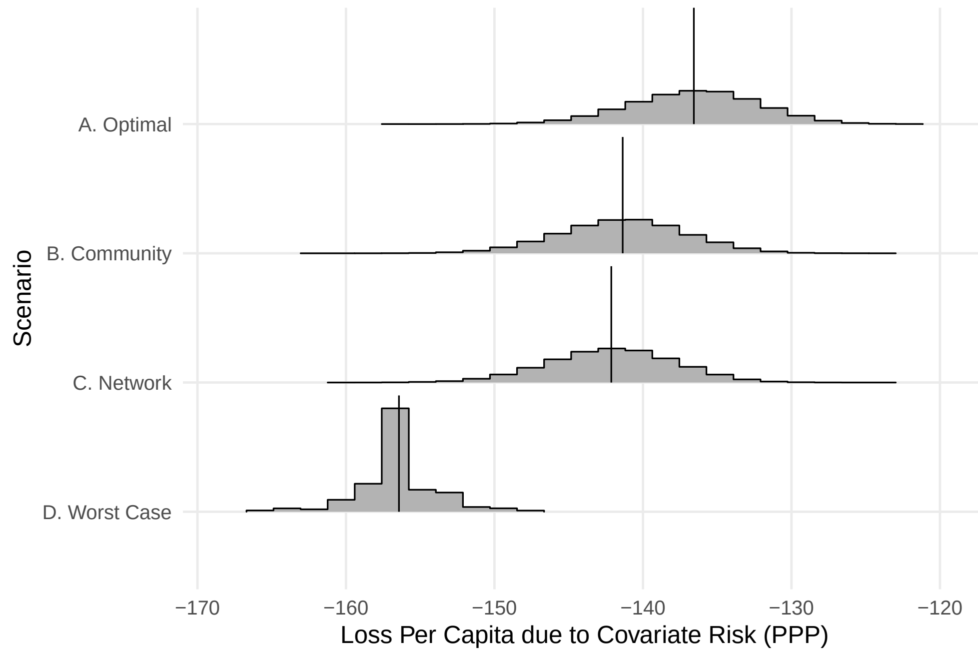


Figure 5: Histogram plots of welfare losses due to risk from 50,000 simulations. Scenario means are denoted by vertical black lines.

available on all questions. Thus, we should be cognizant that at least some of these respondents 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 assortative matching on risk preferences. Figure 8 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 about assortative matching is incomplete. Importantly, I do not model endogenous network formation theoretically. I discuss this issue in detail below. Additionally, though perhaps less pressing, there is the omission of assortivity in the adoption of formal financial products. It is quite plausible that assortivity on other dimensions including savings or access to credit could similarly impact one's ability to share covariate risk. Where risk aversion correlates with these other factors, this would similarly place assortative matching as a barrier to risk sharing.

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 no 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 idiosyncratic 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 drives assortative matching when there is heterogeneity in preferences (Attanasio et al., 2012; Wang, 2015). Similarly, where risk endowments differ, these serve as a driver of assortative matching (Jaramillo et al., 2015; Gao and Moon, 2016). Finally, where shocks are autocorrelated, we may find assortative matching on this dimension (Xing, 2020). This suggests that future avenues may need to balance the apparent substitution between idiosyncratic and covariate risk sharing.

Beyond exploring substitution between forms of risk sharing, the results here may also reflect a multiplexity trap, where risk sharing networks are influenced by other, seemingly unrelated networks (Cheng et al., 2021). For example, risk sharing networks might formed in dyads among co-workers. Such a story would lead to similarly preferenced individuals joining the same risk pools as we seen in our empirical exercise. In such a setting, while endogenous choice is exercised in forming relationships, this choice is both path dependent and may lead to lower utility than if each network were formed independently.

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. While this issue has not been rigorously modeled, intuition might suggest the opposite.[30] For example, if we consider risk sharing as a coping strategy for those excluded from formal risk management tools, we would expect (and possibly hope) that those who are more risk averse would 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.

[30]Some related work has been done. For example, the theoretical model in Jaramillo et al. (2015), which focuses on heterogeneity in risky endowments, relates demand to network structure. They find that those who face the least risk will be accepted by any risk sharing group.

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A Theoretical Appendix

A.1 Risk Sharing in Communities

A.1.1 Focus on Risk Averse Individuals

As presented in Section 3, about 20% of the individuals in the sample are measured as having risk loving preferences. Close readers might reason that these individuals would take on covariate risk from others and would also appreciate the cash to do so. However, I do not model them as so, instead focusing on risk averse individuals. I do this for several reasons, not all of which are explicitly modeled. First, in this model idiosyncratic and covariate risk sharing are a "package deal." That is, to be in the covariate risk sharing arrangement, one must also be in the idiosyncratic risk sharing arrangement. This would serve as a disincentive for these risk loving individuals. Indeed, these individuals are more likely to be isolates in the risk sharing networks (see Table 1).

Second, while the formal model abstracts away from heterogeneity in income variance and downside risk, risk loving individuals' preferences would suggest they would take on more risk (or different kinds of risk, e.g., downside risk). Indeed, we see that risk loving individuals tend to have high income risk (though similar in variance to others who are less risk averse), have greater average losses from risk, and a greater ratio of net losses to net gains (see Table 1). While we do not model heterogeneity in income variance, others do. They find that high risk individuals are included only by those with similar risk profiles: see, for example Jaramillo et al. (2015).

A.1.2 Expected Utility

Because shocks are normally distributed, expected utility for both types is equivalent to maximizing the mean-variance representation as 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 utility function increases in consumption. Thus, the agent consumes all income and transfers available in all states of the world. 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 more risk averse agents when only idiosyncratic risk is pooled is equal to $EU_0 = -\frac{\eta_{2i}}{2}\sigma_c^2$.

A.1.3 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:

$$pc_{1i} + (1-p)c_{2i} \leq \theta\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right) + p\lambda_1 + (1-\theta)\left(\frac{1}{N}\sum_{i=1}^{N}\tilde{y}_i + \tilde{y}_v\right) + (1-p)\lambda_2$$

$$N_1 c_{1i} + N_2 c_{2i} \leq \sum_{i=1}^{N}\tilde{y}_i + N\tilde{y}_v.$$

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

A.1.4 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, FOC 26, and substituting :

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

Finally, I simplify FOC 24 to find θ:

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

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

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

So then we can express the payment between type 1 and type 2 agents:

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

A.1.5 The Rate of Risk Pooling

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

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

A.1.6 Value Functions

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

$$V_1(p, \eta_1, \eta_2) = E(U_1(c_{1i})|\theta^*(p), \lambda_1^*(p)) = \lambda_1^*(p) - \frac{\eta_1}{2}\left(\frac{\theta^*(p)}{p}\right)^2 \sigma_c^2$$
$$= \lambda_1^*(p) - \frac{\eta_1}{2}\left(\frac{p\eta_2}{((1-p)\eta_1 + p\eta_2)p}\right)^2 \sigma_c^2 = \lambda_1^* - \frac{\eta_1}{2}\left(\frac{\eta_2}{((1-p)\eta_1 + p\eta_2)}\right)\sigma_c^2$$

$$
\begin{aligned}
V_1(p,\eta_1,\eta_2) =& \frac{\eta_2}{2}\left(\frac{1-p}{p}\right)\left(1-\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2\right)-\frac{\eta_1}{2}\left(\frac{\eta_2}{(1-p)\eta_1+p\eta_2}\right)^2\sigma_c^2 \\
V_2(p,\eta_1,\eta_2) =& E(U_2(c_{2i})|\theta^*(p),\lambda_2^*(p)) \\
=& \lambda_2^*(p)-\frac{\eta_2}{2}\left(\frac{1-\theta^*(p)}{1-p}\right)^2=\lambda_2^*(p)-\frac{\eta_2}{2}\left(\frac{1-\frac{p\eta_2}{(1-p)\eta_1+p\eta_2}}{1-p}\right)^2\sigma_c^2 \\
=& \lambda_2^*(p)-\frac{\eta_2}{2}\left(\frac{(1-p)\eta_1+p\eta_2-p\eta_2}{(1-p)((1-p)\eta_1+p\eta_2)}\right)^2\sigma_c^2 \\
=& \lambda_2^*(p)-\frac{\eta_2}{2}\left(\frac{(1-p)\eta_1}{(1-p)((1-p)\eta_1+p\eta_2)}\right)^2\sigma_c^2 \\
=& \lambda_2^*(p)-\frac{\eta_2}{2}\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2\sigma_c^2 \\
=& -\frac{\eta_2}{2}\left(1-\frac{\eta_1^2}{((1-p)\eta_1+p\eta_2)^2}\right)-\frac{\eta_2}{2}\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2\sigma_c^2 \\
V_2(p,\eta_1,\eta_2) =& -\frac{\eta_2}{2}\left(1+\left(\frac{\eta_1}{(1-p)\eta_1+p\eta_2}\right)^2\left(\sigma_c^2-1\right)\right)
\end{aligned}
$$

A.2 Optimal Assignment and Village 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, I vary the composition of types in the population in Figure 6. 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 7 demonstrates how the proportion of risk sharing in larger and smaller communities varies 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.

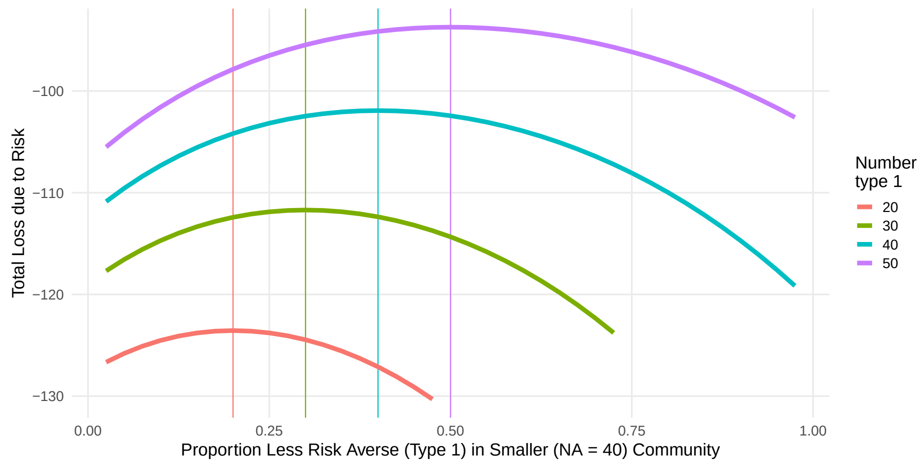


Figure 6: Optimal Allocation of Types Between Unequally Size Communities with varying numbers of type 1 and type 2 agents.

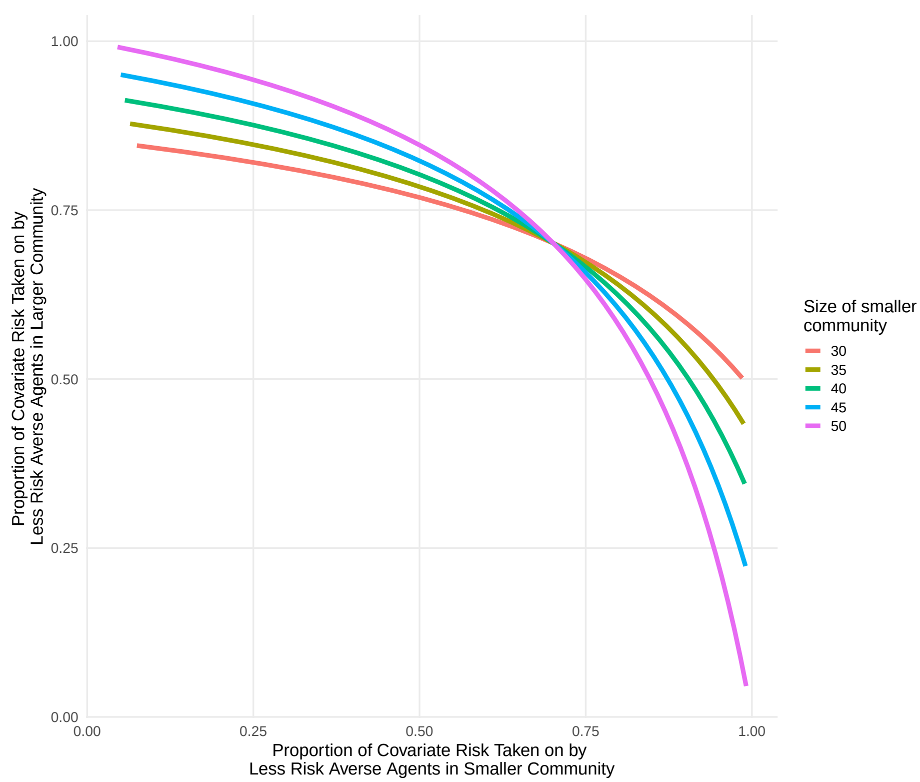


Figure 7: A Risk Management Frontier: Proportion of Covariate Risk Taken on by Less Risk Averse Agents in Communities. From top left to bottom right, type 1 agents move from the larger community to the smaller one.

A.3 The Welfare Implications 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 gamble 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 8 shows how losses due to observed assortative matching increase with risk aversion of more risk averse agents. Furthermore, see Figure 9 which shows a mass of top-coded coefficients of risk aversion.

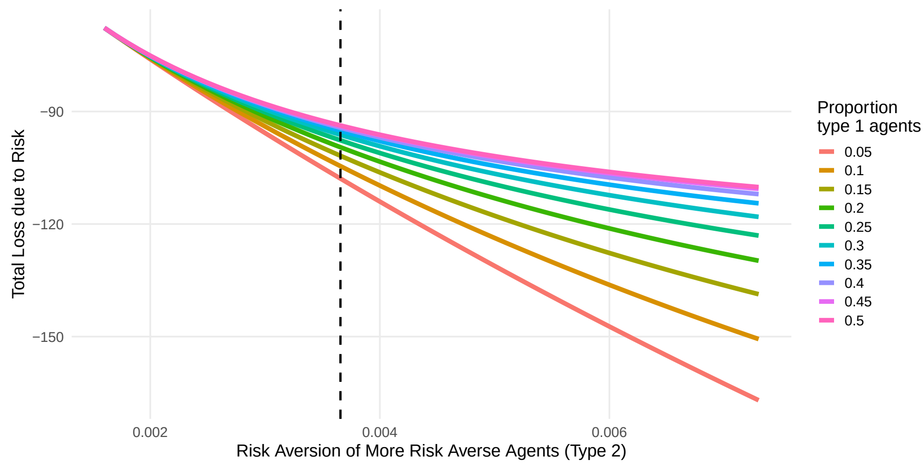


Figure 8: Greater risk aversion increases the welfare impact of assortative matching. As risk aversion increases villages with greater assortative matching will suffer more than those without. However, the delta between degrees of assortative matching is subject to diminishing marginal losses. The dashed vertical line indicates the measured degree of risk aversion among type 2 agents.

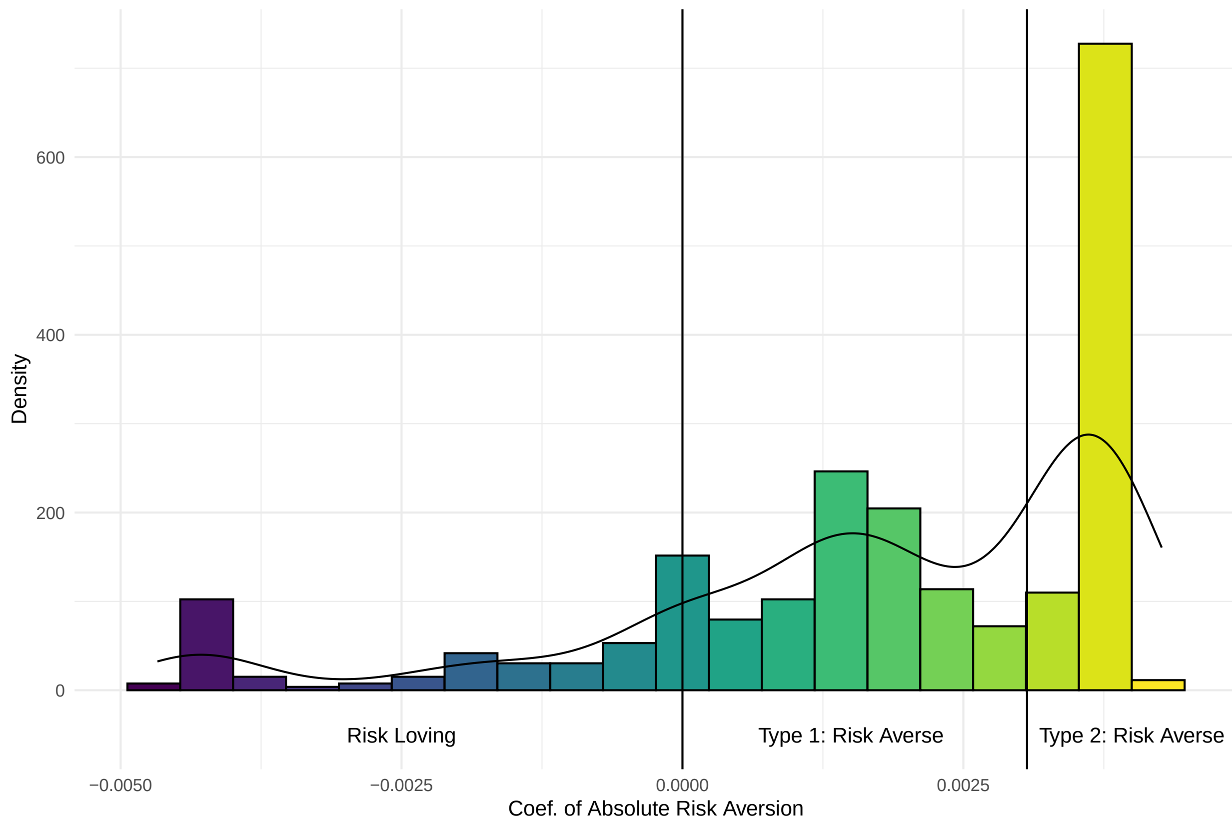


Figure 9: Histogram and distribution of risk preferences within the four villages. The histogram fill, which depicts the measured degree of risk aversion from the hypothetical gambles, is matched with Figures 2 and 10. Vertical lines indicate distinctions between types, which are annotated on the x-axis.

B Empirical Appendix

B.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, and will be indifferent between the two when

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

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.

Table 6: Hypothetical Gamble Questionnaires

		First Questionnaire										
	Prob.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11
y_A	100%	85	90	95	100	105	110	115	120	125	130	135
y_B	50%	20	20	20	20	20	20	20	20	20	20	20
	50%	200	200	200	200	200	200	200	200	200	200	200
		Second Questionnaire										
	Prob.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9		
y_A	100%	80	80	80	80	80	80	80	80	80		
y_B	50%	40	40	40	40	40	40	40	40	40		
	50%	130	125	120	115	110	135	140	145	150		

Each set of questions was asked in the domain of gains and the domain of losses, for a total of four sets of questions. Amounts are in Ghanaian Cedis (about 0.54 GHC/$PPP, so 200 GHC would be around $370 PPP in 2009). The script proceeded from midpoint gamble (Q6 in the first questionnaire and Q5 in the second) to the direction implied. For example, choosing A in Questionnaire 1 Q6 would direct you to Q5, which lowers the sure value of A. The elicitation ends on the question where the respondent switches from their choice.

Amounts for each hypothetical gamble are presented in Table 6. The choice between gambles is framed around choice to purchase agricultural inputs. In the gains domain, the gambles are framed around fertilizer and in the losses domain, they are framed around insecticide. While the gambles themselves are not normally distributed, $y_B - E(y_B)$ is both distributed symmetrically around zero and relatively small compared to incomes.

B.2 Risk Sharing Networks

To construct the gifts network, I use the responses to the question, "Have you ever received a gift (of money, goods, or services) from this person?" In particular, a link occurs in the gift network if i reports receiving a gift from j or j reports receiving a gift from i. To construct the trust network, I report a link if either i and j respond yes to the question "Would you trust this person to look after a valuable item for you?" If a connection occurs in both networks, I record a connection between i and j and use this as my risk sharing network. Future work might utilize the method described in Comola and Fafchamps (2014) to determine how to construct the gifts network. In particular, this approach would draw one additional question from the survey, "Have you ever given a gift (of money, goods, or services) to this person?"

For the family network, I use the relationship codes collected to identify close family. In this definition, family includes spouses, children, step-children, parents, grandparents, and grandchildren. These relationships are lineal and marriage related ties as opposed to collateral ties. Future work might also include some collateral ties such as siblings. The family network is not used to construct the risk sharing network.

B.3 Community Detection

B.3.1 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 B.3.2 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 B.3.3. for the computation of modularity.

B.3.2 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 land on the same nodes. Of course, nodes with higher degree will more often receive these walks, so the measure of distance takes account of 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 its 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, the authors also define the distance between communities:

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

where the source of the random walk is drawn randomly and uniformly from members of that community: $P_{C,k}^s = \frac{1}{|C|}\sum_{i \in C} P_{ik}^s$.

B.3.3 Modularity

Modularity measures the internal quality of the community by looking at how many links exist within the community compared to how many would be expected at random (Newman, 2012). 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 connections in a random graph 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.

B.4 Subgraph Generation Models

B.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 are estimated,

$$\tilde{\beta}_{I,\ell} = \frac{\sum_{i=1}^{n} \mathbf{1}(deg(i) = 0 | l_i = \ell)}{n_\ell} \tag{30}$$

$$\tilde{\beta}_{L,\ell,\ell} = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \times \mathbf{1}(l_i = \ell) \times \mathbf{1}(l_j = \ell)}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{1}(l_i = \ell) \times \mathbf{1}(l_j = \ell)} \tag{31}$$

$$\tilde{\beta}_{L,l,r} = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \times (\mathbf{1}(\ell_i = l) \times \mathbf{1}(\ell_j = r) + \mathbf{1}(\ell_i = t) \times \mathbf{1}(\ell_j = l))}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{1}(\ell_i = l) \times \mathbf{1}(\ell_j = r) + \mathbf{1}(\ell_i = t) \times \mathbf{1}(\ell_j = l)}. \tag{32}$$

For simplicity I index features with s. From proposition C.2 in Chandrasekhar and Jackson (2021) under a sparsity condition[31], $\Sigma^{-1/2}(\tilde{\beta}_n - \beta_0^n) \to N(0, I)$ where β_0^n is the true rate of subgraph generation. For a feature ℓ, the variance of the feature is the entry on the diagonal and the

[31]First, my networks are sparse by the definition of Chandrasekhar and Jackson (2021). 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). Second, 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, noting the sparsity condition may be cracking a walnut with a sledgehammer, so to speak.

standard errors are the square root:

$$\Sigma_{s,s} = \frac{\beta_{0,s}^n(1-\beta_{0,s}^n)}{\kappa_s\binom{n}{m_s}} \text{ and } \tilde{\sigma}_{s,s} = \sqrt{\frac{\tilde{\beta}_s^n(1-\tilde{\beta}_s^n)}{\kappa_s\binom{n}{m_s}}}. \tag{33}$$

where m_s is the number of nodes involved in the feature and κ_s is the number of different possible relabelings of the feature (note: for both isolates and links $\kappa_s = 1$). For the results, $\kappa_s\binom{n}{m_s}$ is the sample size of the feature.

B.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 30, 31, and 32 above. I estimate the coefficient associated with some subgraph s

$$\tilde{\beta}_s = \frac{\sum_{v=1}^4 \text{count}_{sv}}{\sum_{v=1}^4 \text{potential}_{sv}}. \tag{34}$$

This estimate 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

$$\tilde{\sigma}_{s,s} = \sqrt{\frac{\tilde{\beta}_s(1-\tilde{\beta}_s)}{\kappa_s \times \sum_{v=1}^4 \binom{n_v}{m_s}}}. \tag{35}$$

B.4.3 Approximation of Variance of Ratios

I use an approximation of the variance of ratios.[32] 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

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

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.

B.4.4 Relationship of SUGMs to Stochastic Block Models

We can think about how the links and isolates with types model in the community network relates to Stochastic Block Models (SBMs), a generative model for graphs containing communities. We can characterize these SBMs according to a few parameters. For example, the Erdős-Rényi random graph model is simply characterized by n, the size of the graph, and p, the probability of linking between any two nodes in the graph. Another special case is the planted partition model, which can be summarized using p, the probability of linking within community, q, the probability of linking between communities, and $\{n_C\}$, the size of the communities. (This model itself can be represented as a SUGM colored by community membership.) However, in addition to communities, we also have types, which necessitates a more complex representation. In particular, we might characterize it using $\{n_{\ell,C}\}$, the number of type ℓ in community C, $\{p_{\ell,r}\}$ the probability of linking within community between type ℓ and r, $\{q_{\ell,r}\}$, and the probability of linking between communities between type ℓ and type r.

In principle, I could write the SBM representation as a maximum likelihood model. However, for efficiency's sake, instead of recovering communities and affinities from SBM representations, I detect communities and then estimate assortative matching in the community network. Recall that the community network connects all members of the detected communities and none outside. Essentially, this would correspond to a strongly assortative SBM when only considering communities: $p_{\ell,r} = 1$ and $q_{\ell,r} = 0\ \forall \ell, r$ (assortative in the sense that community members tend to link with each other, not in terms of assortative matching on risk preferences). Notably, in the SUGMs, the coefficients are essentially functions of the composition of communities $n_{\ell,C}$, which means that when we estimate we are really just summarizing the composition of communities as assortative matching on risk preferences in a way that can be compared to assortative matching in the risk sharing network.

B.5 Welfare Simulations

B.5.1 Simulation Algorithm

Before simulating, I remove all individuals who do not have preference data or who are not risk averse, and discard resulting communities with only one member.

1. Sort communities into two bins with roughly equal total populations. The first bin will be majority type 1 and the second will be majority type 2. 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 then I construct a running membership sum for each bin. I add a community to bin 1 when $sum_1 \leq sum_2$ and to bin 2 otherwise and proceed until all communities have been added.[33]

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 (i.e., p^U). A success assigns a majority type node to that community while a failure assigns a minority type node.

3. Compute the value functions for type 1 and type 2 agents in each community according to the formulas found in Appendix A.1.6 and average across individuals to determine the per capita losses due to covariate risk. These are reported in units of Purchasing Power Parity (PPP).

Each of these steps is repeated for each repetition of the simulation.

B.5.2 Rate of Between Link Generation

How many connections are there 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

$$\left(\sum_{g=1}^{G} N_{1g}\right)\left(\sum_{g=1}^{G} N_{2g}\right) = N_1 N_2. \;\Rightarrow\; \tilde{\beta}_{1,2} = \frac{\sum_{g=1}^{G} N_{1g}N_{2g}}{N_1 N_2}.$$

[33]Directly minimizing the difference in total membership in type 1 and type 2 majority communities is an np-hard problem. This approach serves as a workaround.

I assume equal parts of 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, I 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 the expression for $\tilde{\beta}_{1,2} = \frac{4}{G} \bar{p}^U \bar{p}^L$.

B.5.3 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 $\frac{\sum_{g=1}^{G} N_g(N_g-1)}{2}$. Suppose also, as above, that $N_g = \frac{N}{G}$. Then,

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

B.5.4 Ratio of Rates

The ratio of rates is

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

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

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

The RHS of the equation lies between 0 and $\frac{1}{4}$. Note that as N becomes large, $\left(\frac{N-G}{N-1}\right) \to 1$. However, the small sample correction does account for the fact that between type connections make up a larger share of connections than within connections (note: 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. Therefore, I leave in the small sample correction. 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:

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

where $p^L \leq 0.5 \leq p^U$.

B.6 Robustness Checks

B.6.1 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 the 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 7 and 8 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, are (additionally) both men, have the same level of schooling, 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 7: 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 are reported in parentheses and are 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. Controls include married, are co-wives, have the same occupation, are the same gender, are both men, have the same level of schooling, 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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: 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 are reported in parentheses and are 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. Controls include married, are co-wives, have the same occupation, are the same gender, are both men, have the same level of schooling, 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.

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

B.6.2 Logistic Regression Results

I estimate assortative matching using a 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 of logistic dyadic regression are estimated for the risk sharing network in Table 9 and the community network in 10. These replicate the pattern of results from the dyadic regressions in the main text. For the risk sharing network, we document assortative 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 9: 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 Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	No
N	71052	71052	71052	71052	71052

t statistics are reported in parentheses and are 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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: 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 Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	No	No
N	71052	71052	71052	71052	71052

t statistics are reported in parentheses and are 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.6.3 Tetrad Logit Results

As a robustness check on the role of degree heterogeneity, I estimate tetrad logit in each village (Graham, 2017).[34] I estimate the models in Python 3.7 using the netrics package.

Turning to the results, in Table 11 Panel A I focus on the estimates unconditional on the sum of risk aversion for each village. Two of these village coefficients 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 Panel B, the change in the estimated 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 Table 12. This is consistent with a situation where measured assortative 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 assortative matching in communities relative to risk sharing networks.[35]

[34] While it is theoretically possible to build an estimate from multiple villages by brute force, a back-of-the-envelope calculation 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.

[35] 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

	Match Between i and j in Risk Sharing Network				Simple Average
	Darmang (1)	Pokrom (2)	Oboadaka (3)	Konkonuru (4)	$=\frac{(1)+(2)+(3)+(4)}{4}$
Panel A: Unconditional Estimates					
$\lvert\eta_i - \eta_j\rvert$	-0.307	0.002	-0.094	-0.098	-0.124
	(0.058)	(0.052)	(0.051)	(0.067)	
Panel B: Conditional Estimates					
$\lvert\eta_i - \eta_j\rvert$	-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	

Standard errors are presented in parentheses below logistic regression coefficients. Fraction of tetrads used denotes the fraction which are selected via the kernel function presented in Graham (2017), and is static across the two regressions.

Table 12: Tetrad Logit with Community Network

	Village				Simple Average
	Darmang (1)	Pokrom (2)	Oboadaka (3)	Konkonuru (4)	$=\frac{(1)+(2)+(3)+(4)}{4}$
Panel A: Unconditional Estimates					
$\lvert\eta_i - \eta_j\rvert$	-0.214	-0.227	0.001	0.064	-0.094
	(0.060)	(0.111)	(0.073)	(0.068)	
Panel B: Conditional Estimates					
$\lvert\eta_i - \eta_j\rvert$	-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	0.013	0.004	0.006	0.013	

Standard errors are presented in parentheses below logistic regression coefficients. Fraction of tetrads used denotes the fraction which are selected via the kernel function presented in Graham (2017), and is static across the two regressions.

B.6.4 Full Results of SUGM Estimation

Table 13: 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 the 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 display the feature, and sample size is that used to estimate the standard errors.

Table 14: 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 the 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 display the feature, and sample size is that used to estimate the standard errors.

Table 15: 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

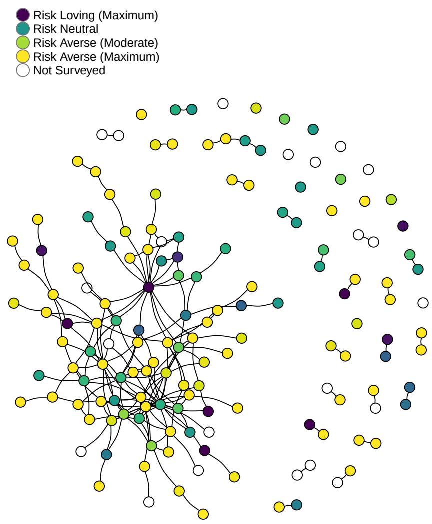
Preferences Pooled SUGM using the risk sharing network with features including links and isolates by whether nodes are less risk averse, more risk averse, are risk loving, or have unmeasured risk aversion (were not surveyed). Count is the number of subgraphs which actually display the feature, potential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

Table 16: Preferences Pooled Subgraph Generation Model with Community Network

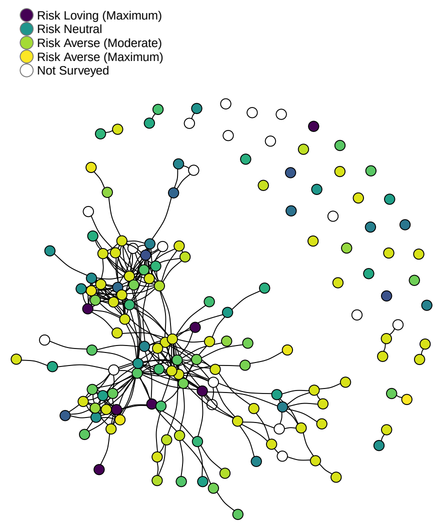
Feature	Count	Potential	Sample Size	Coef.	Std. Err.
Isolates:					
Less risk averse	38	236	631	0.161	0.0146
More risk averse	22	217	631	0.1014	0.012
Not surveyed	39	96	631	0.4062	0.0196
Risk loving	17	82	631	0.2073	0.0161
Within links:					
Less risk averse	893	7511	49536	0.1189	0.0015
More risk averse	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 display the feature, and sample size is that used to estimate the standard errors.

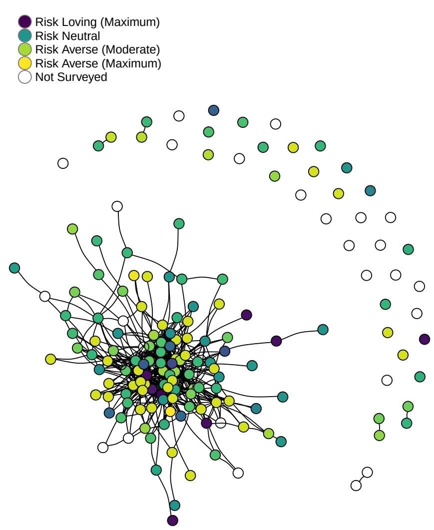
B.7 Network Visualization



(a) Pokrom

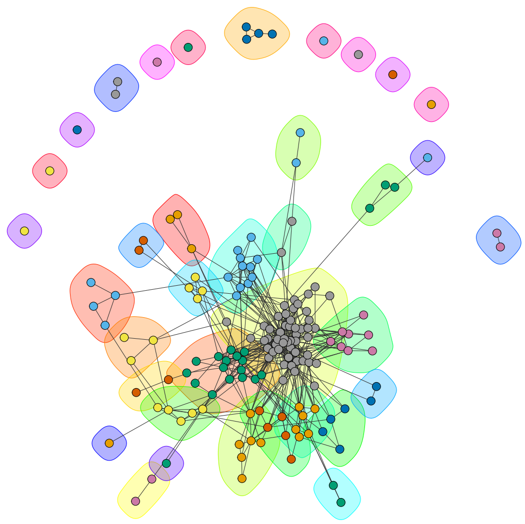


(b) Oboadaka

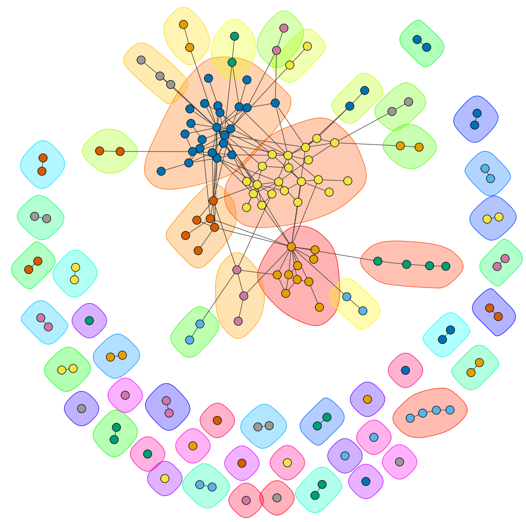


(c) Konkonuru

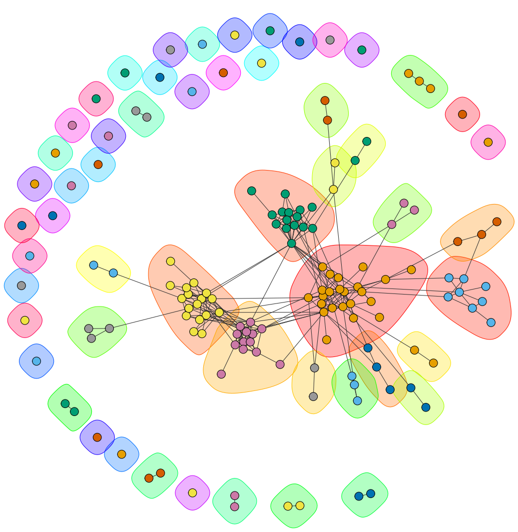
Figure 10: Risk Sharing Networks in Villages with Risk Aversion Indicated by Color



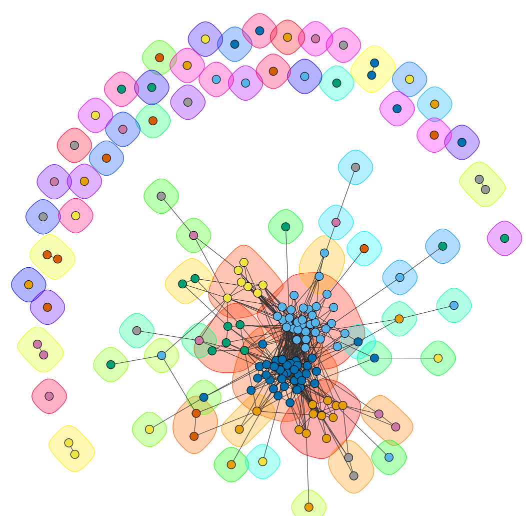
(a) Darmang



(b) Pokrom



(c) Oboadaka



(d) Konkonuru

Figure 11: 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.