Additional Material for Sharing Covariate Risk in Networks: Theory and Evidence from Ghana

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1 Risk Preferences and Prospect Theory

At some point, I considered risk preferences from the perspective of prospect theory, using the fact that games had positive and negative frames. I abandoned this for reasons of complexity and due to the fact that there is some ambiguity about distributions that might span zero for this utility function. Nevertheless, the results of that effort are presented here.

To work in the prospect theory framework, it becomes important to work with a more general form of the exponential utility function. This more general function will be constructed to allow for risk aversion and risk loving behavior and to take into account individuals who have different preferences in the gains and losses domain.

$$u(c) = \begin{cases} \frac{1-e^{-\eta c}}{|\kappa|\eta} & \text{if } c > 0 \\ c & \text{if } c = 0 \\ \frac{1-e^{-\kappa\eta c}}{\kappa\eta} & \text{if } c < 0 \end{cases} \tag{1}$$

Leaving aside risk neutrality, using a set of four hypothetical gambles I can describe 12 different types of agents. Agents are (risk averse in gains, risk loving in gains) $\times$ (risk averse in losses, risk loving in losses) $\times$ (loss averse, loss neutral, loss loving). In general, I lay aside loss aversion and consider four main types of individuals. First, risk averse individuals who are risk averse in both gains and losses ($\eta > 0$, $\kappa > 0$). Second, risk loving individuals who are risk loving in both gains and losses ($\eta < 0$, $\kappa > 0$). Third, prospect theory style individuals who exhibit an S-shaped curve similar to the one discussed in Kahneman and Tversky (1979) ($\eta > 0$, $\kappa < 0$). Fourth, "unicorns" who are risk loving in gains but risk averse in losses ($\eta < 0$, $\kappa < 0$).[1] These potential preferences are plotted in figure 1.

The first two menus presented are in the gains domain. In the first menu, the risky gamble Y_B is held fixed while increasing the sure payment. In the second, the sure payment is held fixed while reducing the upside of the gamble. I assume that if an individual reaches a point of indifference between two gambles, I assign them to the midpoint between the two gambles. Hence, if the mean differs, I take the average of the mean of the two gambles and assign this value to the point of indifference. If the variance differs, I

[1] These unicorns may not be unicorns in situations with small probabilities, as in Kahneman and Tversky's fourfold pattern. This is not our context.

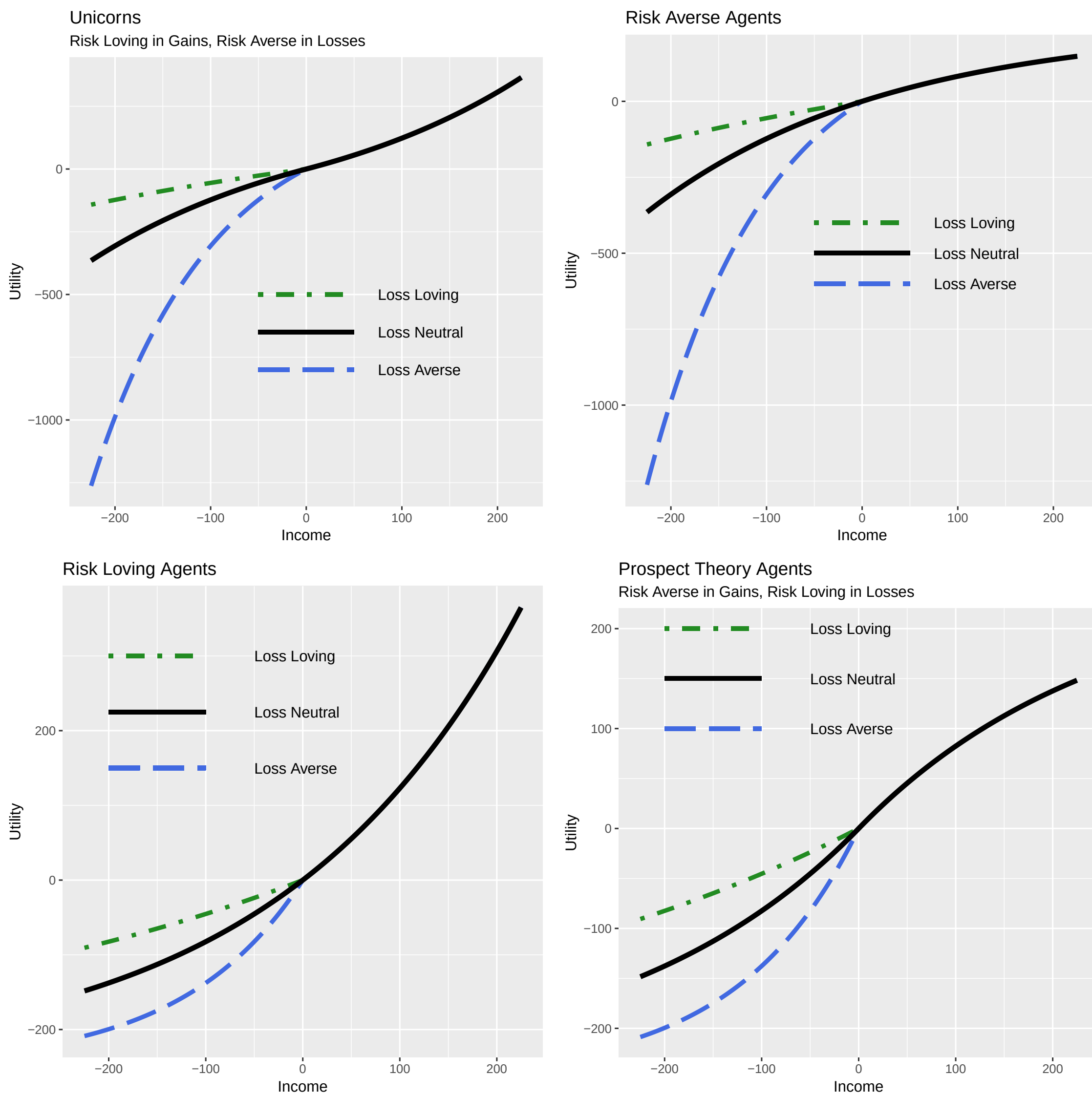

Figure 1: Utility functions of individuals with various types of risk preferences (scaled to be equal in the gains domain).

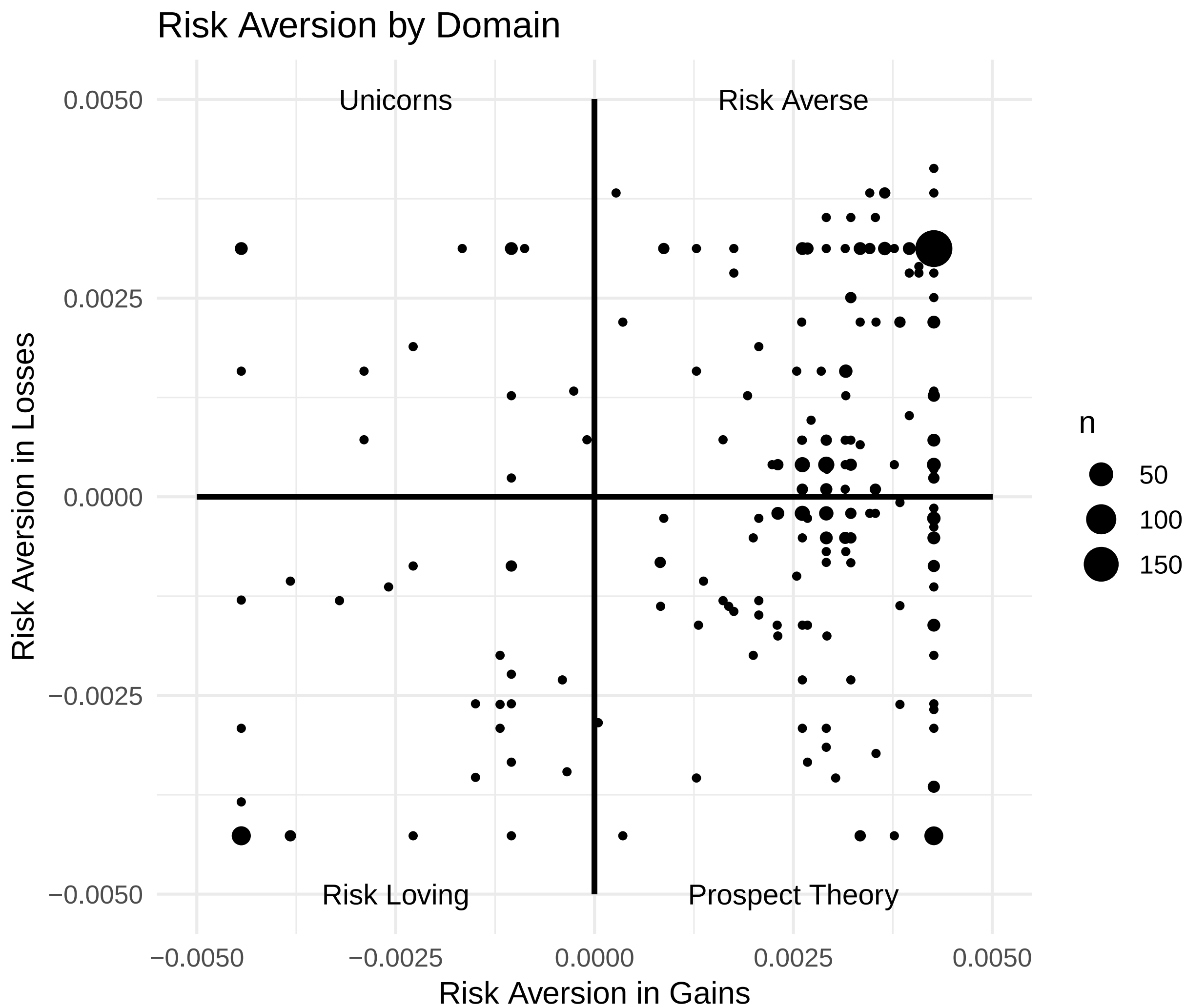

Figure 2: Distribution of individual preference parameters from CARA utility. x-axis corresponds to $\bar{\eta}$, y-axis corresponds to $\bar{\kappa\eta}$.

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.

I compute either $\hat{\eta}$ or $\hat{\kappa\eta}$ (the combined coefficient of risk aversion in the domain of losses) for each lottery and individual. I have two sets of two indifference points, sp to combine these into measures of risk aversion, I average $\hat{\eta}$ and $\hat{\kappa\eta}$ over individuals, and use these averages $\bar{\eta}_i$ $\bar{\kappa\eta}_i$ and individual parameters. I then are able to find the value of $\bar{\kappa}_i$, taking $\bar{\kappa\eta}_i/\bar{\eta}_i$.

I can still represent expected utility as a mean variance utility function in the domain of gains and the domain of losses. In the domain of losses, I write

$$E(Y) - \frac{\kappa\eta}{2}V(Y) \tag{2}$$

I look at a menu of choices between hypothetical gambles. Y_A is a set of sure payments and Y_B is a set of

	Pref. Parameter			
	$\hat{\eta}_a$	$\hat{\eta}_b$	$\hat{\kappa\eta}_c$	$\hat{\kappa\eta}_d$
$\hat{\eta}_a$	1.000	0.703	0.400	0.436
$\hat{\eta}_b$		1.000	0.405	0.409
$\hat{\kappa\eta}_c$			1.000	0.684
$\hat{\kappa\eta}_d$				1.000

Table 1: Pearson correlations between measures of risk aversion based on menus of gambles in the domain of gains and domain of losses.

risky income sources. For mathematical tractability, I assume Y_B is normally distributed. In the domain of gains, respondents are able to choose between these will be indifferent between the two when

$$E(Y_B) - \frac{\eta}{2}V(Y_B) = Y_A \tag{3}$$

Observing this indifference point, I can write

$$\eta = \frac{2(E(Y_{Bg}) - Y_{Ag})}{V(Y_{Bg})} \tag{4}$$

and recover the coefficient of absolute risk aversion. Likewise, in the domain of losses, at the indifference point

$$E(-Y_{Bl}) - \frac{\kappa\eta}{2}V(-Y_{Bl}) = -Y_{Al}. \tag{5}$$

I write

$$\kappa\eta = \frac{2(Y_{Al} - E(Y_B l))}{V(Y_{Bl})} \tag{6}$$

So then κ is the ratio of risk aversion in the domain of gains to risk aversion in the domain of losses. This simplifies to the ratio of the respective risk premiums.

$$\kappa = \frac{E(Y_{Bg}) - Y_{Ag}}{Y_{Al} - E(Y_{Bl})} = \frac{RP_g}{RP_l} \tag{7}$$

Within individuals, measures of risk aversion are highly correlated. For example, in the gains domain the $\hat{\eta}$'s between the two lotteries correlates at a rate of 0.703. Likewise, $\hat{\kappa\eta}$'s correlate at a rate of 0.684. Between the domain of gains and losses, correlations are lower, but still on the order of about 0.4. See Table 1. Of those with full data 313 are risk averse, 127 are prospect theory, 46 are risk loving, and 18 are unicorns. The distribution of preferences is plotted in Figure 2.

2 Tuning the Walktrap Algorithm

While it is difficult to demonstrate every aspect of tuning community detection algorithms, I have in Figure 3 depicted how detected communities differ when the length of random walks increases, using data from a single village.

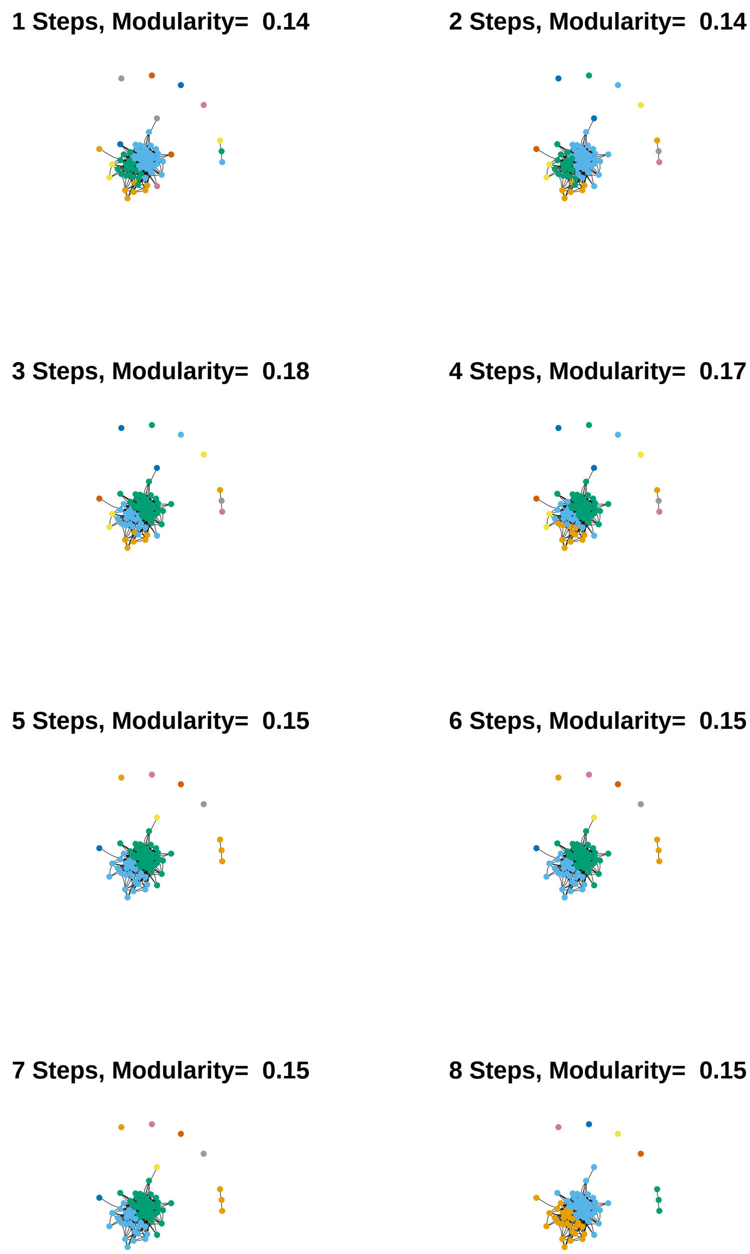

Figure 3: Detected communities using the Walktrap algorithm for a gift network in the village of Darmang. Panels depict walks of different lengths, starting at length 1 and ending at length 8. Within this range, as walks lengthen, the number of communities detected falls from 13 to 7.

3 Household Structure and Networks

An important aspect of this data, as is fully explored by Castilla and Walker (2013), is the household structure of the data. While this does not play a part in my empirical exploration, it is interesting to visualize this aspect of the data. I have done so in Figure 4.

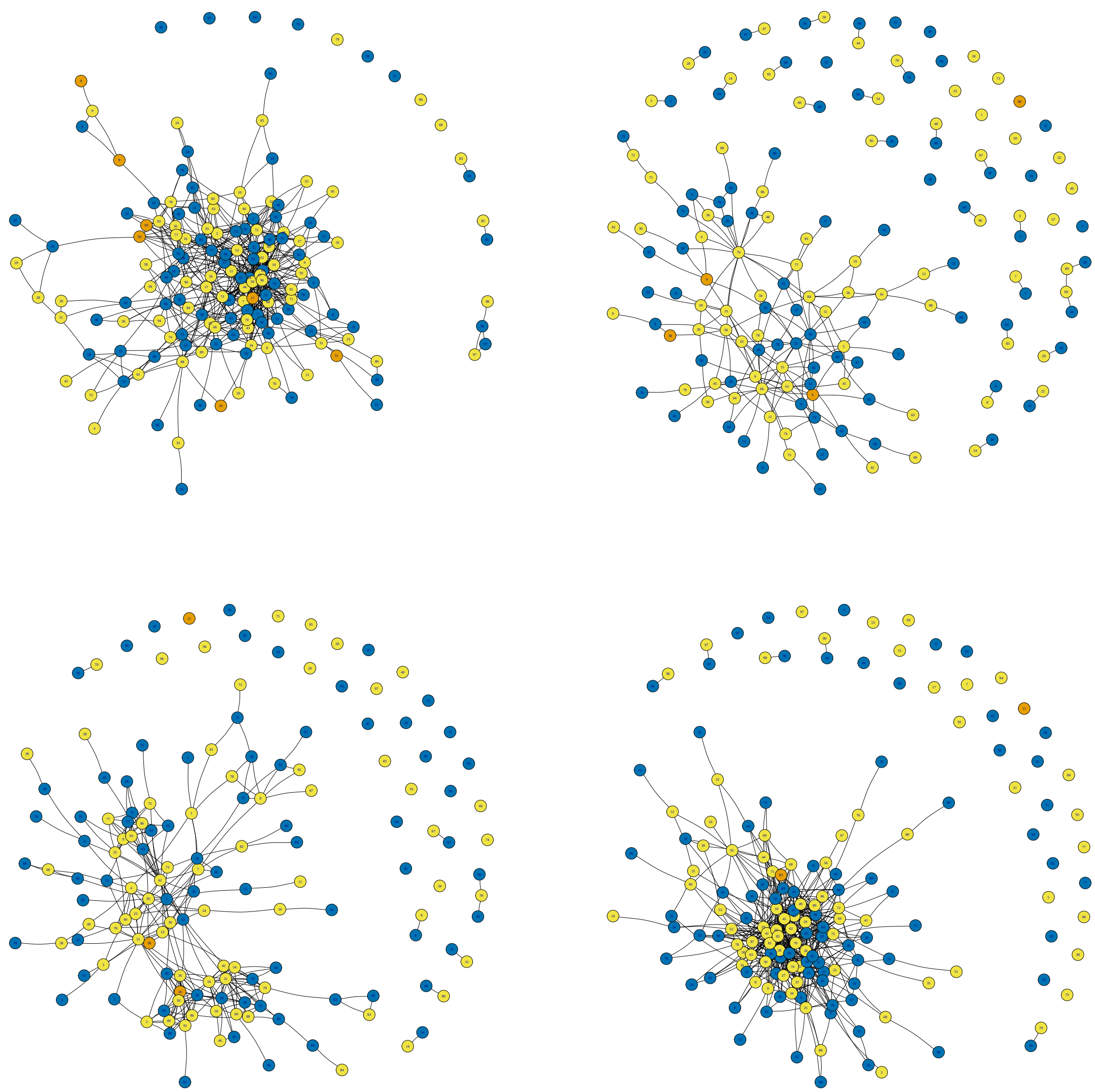

Figure 4: Risk Sharing Networks in Darmang (top left), Pokrom (top right), Oboadaka (bottom left), and Konkonuru (bottom right) with spouses (color = spouse type) and household numbers.

4 Risk Sharing Regressions

At an early stage in this project, I documented idiosyncratic risk sharing within these villages using consumption smoothing regressions. I present these methods and results here.

Testing for the presence of risk sharing, following Kinnan (2021), I use three separate and complementary tests. First, if risk sharing within island is perfect, neither income nor other shocks should effect the consumption of a particular household. Thus these other factors should not enter significantly into the consumption regression when controlling for village-year dummies, community-year dummies and household fixed effects. Conversely, if these variables enter significantly, I conclude that insurance is imperfect at the community level. In my specification, I use only income as an additional explanatory variable. Second, I test the joint significance of time-community fixed effects to test if consumption comoves within communities. Third, I use a version of the contrast estimator presented in Suri (2005), Kinnan (2021) and Boozer and Cacciola (2001).

4.1 Empirical Strategy

4.1.1 Naive Specifications

Following Kinnan (2021), I estimate a total of twelve specifications at the household level. I aggregate all variables over the course of a year. The full specification is as follows:

$$c_{it} = \alpha^W y_{it} + \beta_i + \gamma_{gt} + \delta_{vt} + \varepsilon_{it}. \tag{8}$$

where c_{it} is the ith households' consumption in round t, y_{it} is income, β_i are household level fixed effects, and γ_{gt} are group-round fixed effects. First, I estimate this base specification with only household fixed effects. Second, I estimate the model with village-year fixed effects. Third, I drop village-year fixed effects and add community-year fixed effects. Fourth, I estimate a village averaged model. Fifth, I estimate the community averaged model (with village-year fixed effects).

4.1.2 Measurement Error and Instrumental Variables

Measurement error in this context has the potential to attenuate the magnitude of α^W. This will matter when it comes to tests of risk sharing because the attenuation gives impression that consumption smoothing is better than it is in fact. Thus, for the sixth through tenth specifications, I repeat the above with researcher induced shocks used as an instrument for income. In general, I expect the coefficient on income to rise in these instrumented cases due to measurement error, as is the case in Kinnan (2021).

4.1.3 Tests of Risk Sharing

In these regression equations I am interested in three (necessary but not sufficient) tests for risk sharing: First, significance of a standard t-test of $\hat{\alpha}$. α is inversely proportional to the degree of risk sharing within a community. For perfect risk sharing to exist, I should necessarily fail to reject $H_0 : \alpha = 0$. Other values of $\hat{\alpha}$ between 0 and 1 suggest some (imperfect) degree of consumption smoothing is taking place. This test faces the limitation that it treats all consumption smoothing as risk sharing. To handle this issue, I use a second test for risk sharing. I construct a contrast estimator as used in Suri (2005) and Boozer and Cacciola (2001). I estimate

$$c_{it} = \alpha^{W} y_{it} + \beta_i + \gamma_{gt} + \varepsilon_{it} \tag{9}$$

and

$$\overline{c}_{gt} = \alpha^{B} \overline{y}_{gt} + \nu_{it}. \tag{10}$$

Using the coefficients on the income terms from these regressions results, I can compute a statistic measuring the extent of risk sharing

$$\hat{A} = 1 - \frac{\hat{\alpha}^W}{\hat{\alpha}^B} \tag{11}$$

To test that risk sharing is present, I test $H_0 : A = 0$, computing standard errors using delta method. Third, the joint significance of the community-year dummies by F-test. For risk sharing to be present, these community-year fixed effects need be significant.[2] This test functions similarly to the first test, testing that consumption co-moves within communities. This is not a sufficient test for risk sharing, If risk sharing is taking place, group consumption should do a good job explaining the individual consumption of the group members.

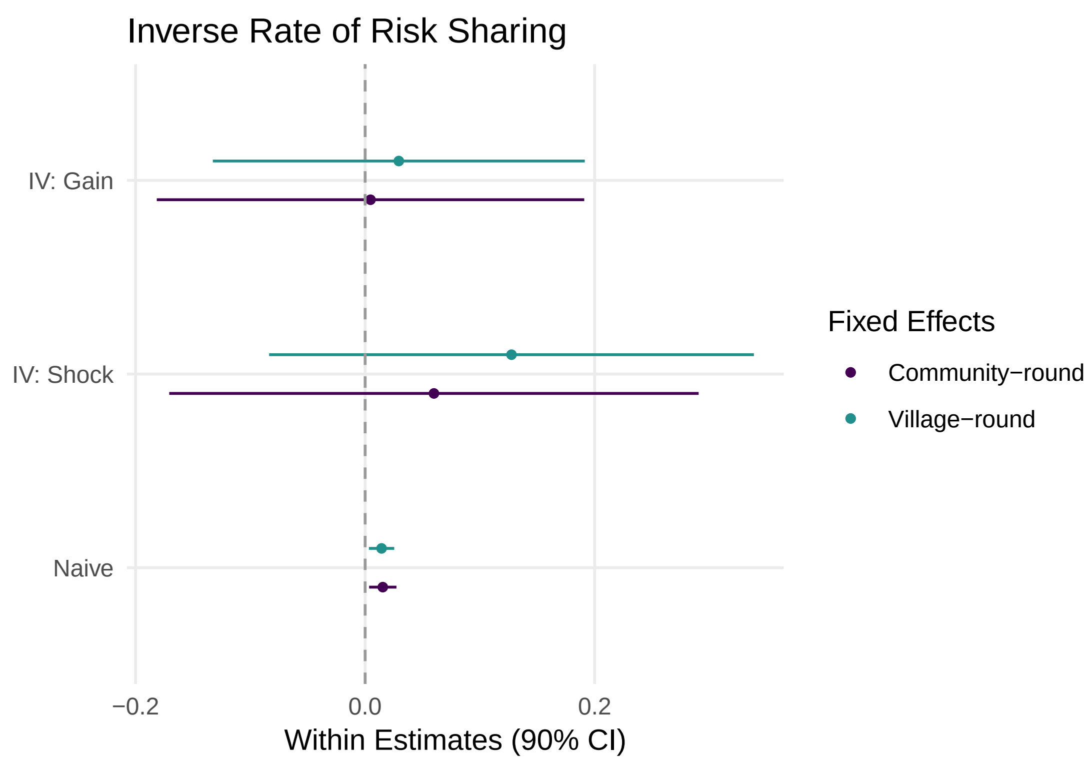

Figure 5: Within Estimates from Risk Sharing Regressions

[2]Note that there are two different tests of significance. One is to test the joint significance of the fixed effects from zero. The second is to test the joint significance of the difference between these fixed effects and the village-time fixed effect. $H_0 : \gamma_{gt} - \bar{\gamma}_v t = 0 \;\forall g, t$.

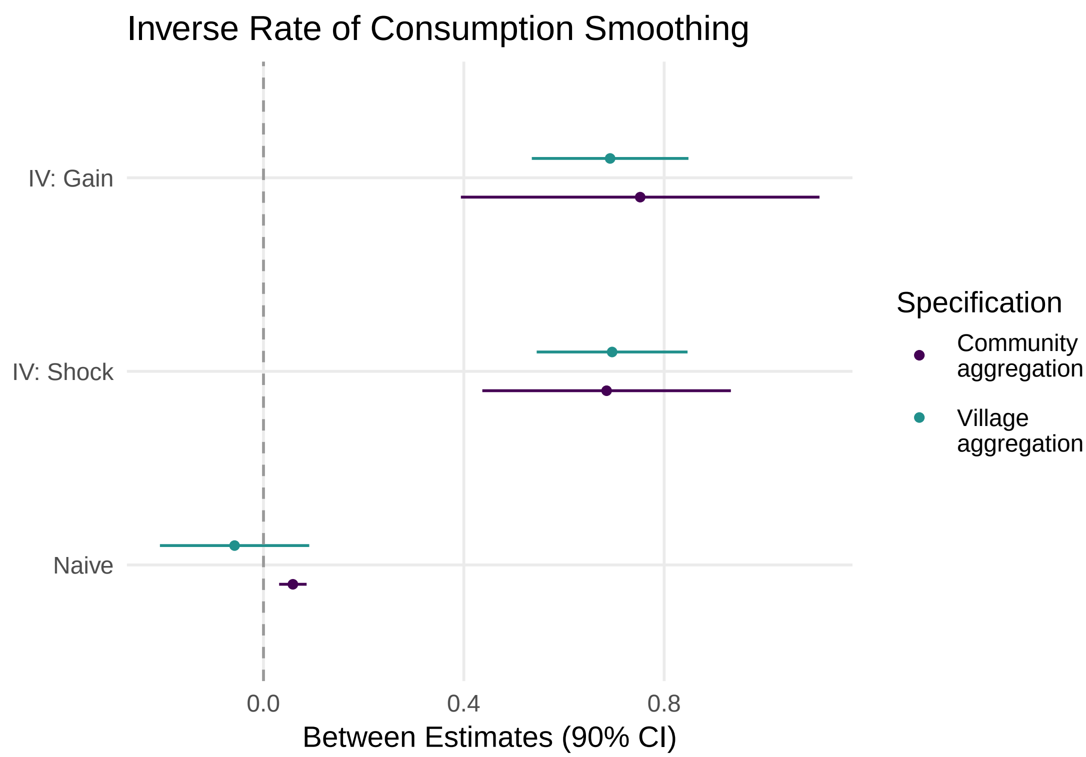

Figure 6: Between Estimates from Risk Sharing Regressions

4.2 Results

I estimate the risk sharing regressions as detailed above and present the results in Tables 2, 5 and 6. These results are also presented in the coefficient plots in Figures 5 and 6.

4.2.1 Naive Estimates

In the naïve (uninstrumented) specification, inverse rates of risk sharing have similar magnitudes across specifications, but perfect risk sharing is rejected in both specifications.

4.2.2 First Stage Estimates

It may be reasonable to worry about weak instrument problems. First, only about 20% of households receive a positive shock. Second, if these gains are relatively private, it could be argued that this would mean they are less likely to be shared to to hidden income Walker and Castilla (2013); Castilla and Walker (2013). F-statistics are calculated per Stock and Yogo (2005) and can be found in Tables 3 and 4. The F-stats for the FE regressions suggest an issue of instrumental relevance, which may suggest bias in the IV estimates. In the case of the aggregated village and community level regressions, however, the IV regressions feature sufficiently large F-stats. Based on relevance, we prefer the gain instrument to if there was any shock.

Table 2: Risk Pooling Regressions: Naive Specification

	Food Expenditure				
	(1)	(2)	(3)	(4)	(5)
Income	0.014**	0.014**	0.015**	−0.058	0.059***
	(0.006)	(0.006)	(0.006)	(0.076)	(0.014)
Constant				299.306***	228.664***
				(30.931)	(8.463)
Household FE	Yes	Yes	Yes		
Village-round FE		Yes			
Community-round FE			Yes		
Aggregation	HH	HH	HH	Village	Community
Observations	1,568	1,568	1,566	20	311
R^2	0.561	0.583	0.644	0.031	0.054
Adjusted R^2	0.448	0.468	0.445	−0.023	0.051

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 3: First stage estimates from instrumenting income with any positive shock

	Income				
	(6)	(7)	(8)	(9)	(10)
Postive Shock	119.756*	140.051**	129.963*	2,123.777***	518.586***
	(64.448)	(66.114)	(77.386)	(350.580)	(101.698)
Household FE	Yes	Yes	Yes		
Village-round FE		Yes			
Community-round FE			Yes		
Aggregation	HH	HH	HH	Village	Community
Observations	1,568	1,568	1,566	20	311
F(1,df) (excluded)	3.453	4.487	2.82	36.698	26.003
R^2	0.720	0.725	0.752	−2.129	−0.124
Adjusted R^2	0.648	0.650	0.613	−2.294	−0.128

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 4: First stage estimates from instrumenting income with the gain from any positive shock

	Income				
	(6)	(7)	(8)	(9)	(10)
Gain	0.619**	0.637**	0.588**	15.320***	3.078***
	(0.263)	(0.265)	(0.290)	(2.826)	(0.818)
Household FE	Yes	Yes	Yes		
Village-round FE		Yes			
Community-round FE			Yes		
Aggregation	HH	HH	HH	Village	Community
Observations	1,568	1,568	1,566	20	311
$F(1,\text{df})$ (excluded)	5.54	5.78	4.124	29.385	14.151
R^2	0.720	0.726	0.753	−2.602	−0.165
Adjusted R^2	0.648	0.650	0.614	−2.792	−0.169

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.2.3 IV Estimates

When income is instrumented for with shocks to income, inverse coefficient estimates tend to increase. If positive shocks are a valid instrument, this suggests worries about (classical) measurement error tend be well founded. Looking at the naive specifications, we reject perfect risk sharing (significant at the 5% level) in all three household level regressions. The magnitudes of the inverse rate of risk sharing are very small, however, and tend to be similar across specifications. For example in the village-round specification, $\hat{\alpha} = 0.014$, implying consumption is smoothed at a rate of 0.986.

Even when instrumenting income, we often fail to reject the null of perfect risk sharing, even as estimated magnitudes of the rate of inverse risk sharing rise. When instrumenting for income with whether or not a positive shock occurred, the rate of inverse risk sharing in the village-round specification rises to 0.113, while the community level estimate rises to 0.072. When instrumenting with gain, the rate of inverse risk sharing in the village-round specification rises to 0.031, while the community level estimate rises to 0.011. None of these coefficient estimates are statistically significant. We do see that coefficient estimates from the community-round regressions are smaller than their counterparts in the village-round regressions.

4.2.4 Contrast Estimators

At the village level the contrast estimators are $\hat{A}_v = 1.248$, and $\hat{A}_{v,IV} = 0.809$ and $\hat{A}_{v,IV2} = 0.956$ when using total gain as an instrument. The contrast estimator from the naïve regressions seem to an issues. In theory, the coefficient on $\hat{\alpha}^B \geq 0$. At the community level, the contrast estimators are $\hat{A}_g = 0.743$ and $\hat{A}_{g,IV} = 0.894$ and $\hat{A}_{g,IV2} = 0.985$ using gain as an instrument.

Table 5: Risk sharing results from instrumenting income with any positive shock

	Food Expenditure				
	(6)	(7)	(8)	(9)	(10)
Income	0.056	0.128	0.060	0.696***	0.685***
	(0.111)	(0.108)	(0.118)	(0.077)	(0.127)
Household FE	Yes	Yes	Yes		
Village-round FE		Yes			
Community-round FE			Yes		
Aggregation	HH	HH	HH	Village	Community
df	1246	1230	1002	19	310
Observations	1,568	1,568	1,566	20	311

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6: Risk sharing results from instrumenting income with the gain from any positive shock

	Food Expenditure				
	(6)	(7)	(8)	(9)	(10)
Income	0.007	0.029	0.005	0.692***	0.752***
	(0.086)	(0.083)	(0.095)	(0.080)	(0.183)
Household FE	Yes	Yes	Yes		
Village-round FE		Yes			
Community-round FE			Yes		
Aggregation	HH	HH	HH	Village	Community
df	1246	1230	1002	19	310
Observations	1,568	1,568	1,566	20	311

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

References

M. Boozer and S. Cacciola. Inside the 'Black Box' of Project STAR: Estimation of peer effects using experimental data. *Yale Economic Growth Center Discussion ...*, (832), 2001. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=277009.

C. Castilla and T. Walker. Is Ignorance Bliss? The Effect of Asymmetric Information between Spouses on Intra-Household Allocations. *American Economic Review*, 103(3):263–268, 2013. ISSN 0002-8282. doi: 10.1257/aer.103.3.263. URL http://pubs.aeaweb.org/doi/10.1257/aer.103.3.263.

D. Kahneman and A. Tversky. Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2): 263–292, 1979. ISSN 0012-9682. ISBN: 0521627494.

C. Kinnan. Distinguishing barriers to insurance in Thai villages. *Journal of Human Resources*, 57(1):44–78, 2021. doi: 10.3368/jhr.57.1.0219-10067R.

J. H. Stock and M. Yogo. Testing for weak instruments in linear IV regression. (February):80–108, 2005.

T. Suri. Spillovers in village consumption: Testing the extent of partial insurance. Technical report, 2005.

T. Walker and C. Castilla. Gender Roles and Asymmetric Information: Non-Cooperative Behavior and Intra-Household Allocation. Technical report, 2013. Issue: July.