Spatial vs. Social Network Effects in Risk Sharing†

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Abstract

Although substantial research has been conducted on informal consumption smoothing within villages or within social clusters such as family and friends, few studies have compared the effects of these spatial and social networks. Employing spatial panel econometric models, this study extends the empirical test of the full risk-sharing hypothesis to incorporate spatial and social network effects and quantifies the diffusion of income shocks in each network. Estimation results based on household survey data in Southern Sri Lanka show that consumption smoothing performs better in spatial networks than in social ones, because income shocks defuse better among neighboring households. This study also shows the limitations of the conventional test when it is considered a special case of a spatial econometric model.

Keywords: Risk sharing; network; distance; kinship; spatial panel econometrics; externality

JEL classification: O12; Q12; C23

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1. Introduction

Although rural households in developing countries face various types of risks, formal institutions that can mitigate these risks are often weak. Under such situations, informal consumption smoothing, that is, risk sharing, is critical. Townsend (1994) conducted the seminal work in this field by applying the full risk-sharing hypothesis (FRSH) to micro data in India. Although he rejects the FRSH, he also finds that the effects of income shocks on individual consumption are very small. Despite some cases where the FRSH cannot be rejected, many subsequent studies reach almost similar results to those of Townsend (1994) (e.g., Udry 1994; Townsend 1995; Ravallion and Chaudhuri 1997; Grimard 1997; Deaton 1997; Jalan and Ravallion 1999; Kurosaki 2001). To investigate the mechanism of this "partial risk-sharing" situation, several studies have focused on types of frictions in risk-sharing arrangements, such as private information (Ligon 1998) and limited commitment (e.g., Kocherlakota 1996; Foster and Rosenzweig 2001; Ligon et al. 2002; Dubois et al. 2008; Laczó 2013), and others have recently compared the effects of these barriers (Kinnan 2012; Karaivanov and Townsend 2013).

This study provides an alternative approach to the risk-sharing test that incorporates spatial and social network effects by employing a spatial panel econometric approach. These networks are important to mitigate the problems of asymmetric information and limited commitment.

Spatial networks are important because of transaction costs in risk-sharing arrangements. Because financial systems and infrastructures are underdeveloped in developing countries, the issues of transaction costs are more salient (e.g., Jack and Suri 2014). Under such conditions, spatial distance serves as a proxy of transaction costs, because it increases costs associated with asymmetric information and contractual enforcement problems (Rosenzweig 1988; Townsend 1995). Murgai et al. (2002) analyze the optimal risk-sharing group size under the existence of two types of transaction costs: "association" costs of establishing links with insurance partners and "extraction" costs of implementing transfers, such as monitoring and rule enforcing. They find that these transaction costs, measured by physical distance, have a negative effect on risk-sharing group formation. De Weerdt (2004) and Fafchamps and Gubert (2007) also test the effects of spatial distance on dyadic risk-sharing network formation, and find that higher costs (i.e., larger distance) prevent households from forming links. However, these studies mainly focus on group formation and do not analyze co-movement in consumption or the effect of individual income shocks. Thus, bridging these studies and the conventional tests of the FRSH should be addressed.

Although many previous studies have focused on intra-village risk sharing, social networks also play an important role especially under the limited commitment problem, because family ties and altruism facilitate income transfer among households with different realized income (e.g., Cox and Fafchamps 2008; Fafchamps 2011). For example, Grimard (1997) applies the FRSH to ethnic groups in Cote d'Ivoire and confirms a partial risk-sharing situation. Foster and Rosenzweig (2001) show that altruism based on family ties serves to ease the commitment problem. Fafchamps and Lund (2003) show that households receive gifts and informal loans through networks of friends and relatives. Angelucci et al. (2012) show that resources are well shared in extended family networks and that the positive spillover effect through the risk-sharing mechanism leads to higher human capital investment. In terms of network formation, De Weerdt (2004) and Attanasio et al. (2012) find that close friends and relatives tend to form risk-pooling groups.

Although these previous studies have emphasized the importance of both spatial and social networks, few have compared the effects of these networks based on the FRSH test. In order to fill this gap and incorporate these spatial and social network factors into an empirical model, this study employs a spatial panel econometric approach. Spatial econometrics focuses on spatial effects resulting from spatial dependence and heterogeneity (e.g., Anselin 1988; LeSage and Pace 2009). Recently, studies have been shifting to panel data analysis, and estimation methods have been developed (e.g., Elhorst 2003, 2010; Kapoor et al. 2007; Anselin et al. 2008). By employing these models, this study analyzes whether there are any spatial and social network effects in risk-sharing arrangements.

One of the most important objectives of employing spatial econometric models is the estimation of direct and indirect effects. If risk-sharing mechanisms work, albeit partially, individual income shocks have externalities, affecting other households' consumption. Angelucci and De Giorgi (2009) and Angelucci et al. (2012) show that a cash transfer program indirectly affects ineligible households' consumption through the risk-sharing mechanism. They articulately identify the treatment effect by comparing the outcomes of the ineligible in the treatment and control villages. In contrast, this study quantifies the external effects of income shocks based on the FRSH test, providing a mechanism treated as a black box in previous studies. By estimating direct and indirect effects, which are common approaches in spatial econometrics literature, we can quantify this external effect as well as direct effects of individual shocks, and we can compare the effects of income shock diffusion in spatial and social networks.

The remainder of this paper is organized as follows. Section 2 describes the conventional empirical test of the FRSH and the empirical strategy of this study. Section 3 describes the dataset used in this study, and Section 4 discusses the empirical results. The final section offers a summary and concluding remarks.

2. Empirical Strategy

The benchmark model is the conventional FRSH test, which is a standard model adopted in previous studies[1] (e.g., Mace 1991; Cochrane 1991; Townsend 1994; Kurosaki 1999). Suppose that an economy consists of N households (i = 1, …, N) with a von Neumann-Morgenstern utility function, u_i, where $u_i' > 0$ and $u_i'' < 0$. There is a finite set of states s = {1, …, S}, each of which occurs with probability π_{st}. In each state, households receive stochastic income y_{ist} and consume c_{ist}. The Pareto optimal resource allocation is obtained by solving the following social planner's problem:

$$\max \sum_{i=1}^{N} \lambda_i \sum_{t=1}^{\infty} \rho_i^t \sum_{s=1}^{S} \pi_{st} u_i(c_{ist})$$

with the resource constraint

$$\sum_{i=1}^{N} c_{ist} \leq \sum_{i=1}^{N} y_{ist}$$

where λ_i is a Pareto weight and ρ_i is the discount factor of household i. The interior solution of this problem requires satisfying the following first order condition:

$$\lambda_i \rho_i^t u_i'(c_{ist}) = \mu_{st}, \quad \forall i,$$

where μ_{st} is the Lagrange multiplier divided by π_{st}. This condition means that the weighted marginal utility is equalized for all i, implying that idiosyncratic income shocks do not affect individual consumption under the FRSH.

Assuming the forms of a utility function, empirical tests of the FRSH can be derived from these conditions. If the utility function is the constant absolute risk aversion (CARA) type, individual consumption level co-moves with the average consumption level in the economy, and idiosyncratic shocks in income should not affect consumption[2]. Assuming

[1] The following notation is based on Kurosaki (1999).
[2] See Appendix for the results employing a CRRA utility.

homogenous preference parameters, the empirical test equation is as follows:

$$c_{it} = \beta \overline{c_t} + \gamma y_{it} + \eta_i + \varepsilon_{it}$$

where $\overline{c_t}$ is the within-cluster average of consumption level at *t*, y_{it} is household *i*'s income at *t*, and η_i are individual fixed effects. In order to avoid a spurious correlation problem, these average values are calculated without household *i*. If the FRSH holds, individual consumption should perfectly co-move with the average income, and idiosyncratic income shock should not affect individual consumption. Therefore, we can test the FRSH by estimating this model and testing $\beta = 1$ and $\gamma = 0$.

In order to incorporate spatial and social network factors into the empirical test model, this study employs a combined spatial lag and error model, also called as an SAC model (LeSage and Pace 2009), with household fixed effects:

$$c_t = \beta W c_t + \gamma y_t + \eta + u_t$$
$$u_t = \lambda W u_t + \varepsilon_t$$

where *W* is a spatial weight matrix and η is a vector of household fixed effects. This model nests a spatial autoregressive model (SAR) when $\lambda = 0$. For estimation, this study employs a maximum likelihood approach. In order to handle the incidental parameter problem, the transformation approach proposed by Lee and Yu (2010) is used for bias correction.

The important point of this approach is that conventional FRSH tests are special cases of this model when there is no spatial correlation in the error term ($\lambda = 0$), and the weight matrix is defined as

$$w_{ij} = 1/(N_c - 1) \text{ if } (i,j) \in c \text{ for } \forall i \neq j$$
$$w_{ij} = 0 \text{ otherwise}$$

where *c* is the set of risk-sharing clusters, and N_c is the number of households in the same cluster. Thus, the conventional models implicitly assume that (1) there are no spatial correlations in the error term, (2) changes in consumption have identical effects among the members in the same cluster, and (3) there is no risk sharing across clusters. Note that this matrix is the row-standardized version of the adjacency matrix whose element is 1 if *i* and *j* belong to the same cluster, and 0 otherwise.

Considering the conventional tests as spatial econometric models causes another problem in the estimation. Previous studies employing the conventional tests have estimated the models using ordinary least squares (OLS). However, under the existence of spatial dependence, OLS estimators are known to be inconsistent (Anselin 1988). By comparing the estimation results of the OLS and spatial econometric versions, this study can discuss the bias of the conventional tests.

In addition to the block-based weight matrix, this study uses an inverse distance matrix as another method for capturing the spatial network effect. In the case of risk sharing, it is natural to assume that transaction costs are increasing functions of the distance among each household (e.g., Rosenzweig 1988; Murgai et al. 2002; Fafchamps and Gubert 2007). For example, neighboring households can easily monitor each other to mitigate the moral hazard problem and to implement risk-sharing contracts. Thus, under the existence of transaction costs, the consumptions of neighboring households are more likely to co-move than those of distant households. Note that the conventional test assumes perfect co-movement of the consumptions of households in the same cluster regardless of distance. Regarding the spatial correlation in unobserved factors, neighboring households tend to face the same spatially covariate shocks. In order to reflect these factors and assign larger values to nearer households, an inverse distance matrix based on GPS data is used as a weight matrix.

Regarding social networks, this study uses an adjacency matrix based on kinship. This type of network is important because extended families might be connected altruistically, and the tie can facilitate income transfer in a risk-sharing arrangement (e.g., Foster and Rosenzweig 2001; Cox and Fafchamps 2008; Fafchamps 2011). Thus, households connected in terms of kinship tend to share risks, which results in co-movement of consumption. Using this matrix enables us to analyze these effects quantitatively.

In addition to estimating these models, this framework enables us to estimate direct and indirect effects. Under the existence of a risk-sharing mechanism, individual income shocks not only affect consumption of the said household but also that of neighboring households. However, few studies examine these effects quantitatively. Using the estimation results of spatial econometric models, this study estimates the direct ($= \partial c_{it}/\partial y_{it}$) and indirect effects ($= \sum_{i \neq j} \partial c_{it}/\partial y_{jt}$). Based on the literature of spatial econometrics (e.g., LeSage and Pace 2009), our study specifies these effects as follows:

$$\bar{M}_{direct} = n^{-1} tr(S(W))$$
$$\bar{M}_{total} = n^{-1} \iota_n' (S(W)) \iota_n$$
$$\bar{M}_{indirect} = \bar{M}_{total} - \bar{M}_{direct}$$

where $S(W) = (I_n - \beta W)^{-1} I_n \gamma$ and ι_n is a vector of ones. Comparing these effects, this study can quantify the spatial and social externalities of income shocks.

Table 1 summarizes the expected results from each hypothesis. In the case of the FRSH, the coefficient on the spatial lag is 1, and that on income is 0. Thus, both direct and indirect effects are also 0. In a partial risk-sharing case, the coefficients on both spatial lag and income are positive, which results in positive direct and indirect effects. If there is no risk sharing (i.e., autarky), i's consumption is determined only by his/her own income, implying that the coefficient on the spatial lag is 0. Thus, the indirect effect is also 0 despite that the direct effect is equal to the coefficient on income.

3. Data

This study uses a dataset collected by JICA (former JBIC) as part of the research project "Impact Assessment of Infrastructure Projects on Poverty Reduction"[3]. The study site is Walawe Left Bank (WLB), which is located in the southern part of Sri Lanka. Using Japanese ODA loans, the government started to construct the Left Bank Main Canal in 1995, and most households had received access to irrigation water by 2008.

In order to assess the effects of this project, JICA conducted eight household surveys covering seven cropping seasons, collecting data that included the households' demographic information and their seasonal income and consumption. Because the consumption module of the questionnaire was modified in the last survey round, this study uses panel data of the former seven rounds. The original sample size was 858 households in the first four rounds, and 193 households in the next two rounds. Of the 193 households, both GPS and balanced panel survey data were available for 171 households after dropping missing observations. The locations of each household are shown in Figure 1. The average distance among households is 10.17 km with a standard deviation 7.35.

Figure 2 shows the kinship network among the heads of the sample households[4]. The network density, defined as $2m/n(n-1)$, where m is the number of edges in the

[3] See JBIC Institute (2007) for details of this project.

[4] In this study, the definition of kinship is father/mother, uncle/aunt, cousin, grandfather/grandmother, son/daughter, nephew/niece, grandson/granddaughter, brother/sister, and other extended relationship. Because of reporting errors, the matrix is not symmetric. I tested robustness by replacing the asymmetric entries with 0, 0.5, or 1, and found that the main findings were not affected very much.

network, is 0.279. Among 171 households, 49 do not have kin in the sample.

The study site is divided into five blocks according to their accessibility to irrigation: Sevanagala Irrigated, Sevanagala Rainfed, Kiriibbanwewa, Sooriyawewa, Mayurapura, and Tissapura. This study uses these blocks as clusters of risk sharing. Because the irrigation canal was originally constructed from the upstream area and gradually extended downstream, there are time lags in the irrigation access among each block. Table 2 summarizes the timing of the irrigation access in each block. Specifically, Sevanagala Irrigated, Kiriibbanwewa, and Sooriyawewa were already irrigated by the first round. Mayurapura accessed irrigation water by the sixth round, and Tissapura did so by the last round. Because of topographical constraints, irrigation access was not available in Sevanalgara Rainfed for the sample period.

Table 3 shows the descriptive statistics of the variables used in this study. The total sample size is 1026 (171 households $\times$ 6 cropping seasons). Following previous studies, this study uses adult-equivalent consumption and income based on the age and sex weights in Townsend (1994). This consumption includes self-produced items, and both consumption and income levels are adjusted for the price index based on 2005 Sri Lanka Rupees[5]. The net incomes are negative for 7.4% of the samples, because their agricultural input costs exceed the total value of production. This is typically true of farmers who started banana cultivation, which is the second most popular crop in the region after paddy, because of the large initial cost.

Table 4 shows Moran's *I* for the transient change in income and consumption, which is defined as the difference between the adult-equivalent income/consumption at time *t* and its average over six seasons.[6] Changes in income tend to co-move according to the spatial network, that is, the block-based and inverse distance matrices, though the magnitudes are very small. Because a substantial number of households earn the largest share of their income from agriculture in the study area (Sellamuttu et al. 2013), there are some spatially covariate shocks that affect agricultural productivity, such as bad weather and crop disease (e.g., Druska and Horrace 2004). Food consumption tends to co-move both spatially and socially. In some cases, correlation in food consumption is significant even when income changes are not correlated. This implies that idiosyncratic shocks are diffused in networks

[5] The source is http://www.indexmundi.com/facts/sri-lanka/consumer-price-index

[6] The Moran's *I* statistic is a measure of spatial correlation defined as

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})}.$$

because of the risk-sharing mechanism. Non-food consumption is also correlated, especially according to the inverse distance matrix. Although these casual observations support the existence of a risk-sharing mechanism, formal testing based on the FRSH models is still required.

4. Estimation Results

4.1 Baseline Results

Using the described dataset, this section estimates the conventional FRSH test and the SAR and SAC models. This study uses three different weight matrices: (1) the block-based matrix, whose element takes 1 if i and j live in the same block; (2) the inverse distance matrix, whose elements are calculated based on GPS data; (3) the kinship matrix, whose element takes 1 if i and j are kin. (1) and (2) capture spatial networks and (3) captures social networks. These matrices are row-standardized for the estimation. As previously mentioned, the estimation results of the conventional test might be biased when the test is regarded as a spatial econometric model. Thus, comparing the results of the conventional test and the SAR model with the block-based matrix, which corresponds to the spatial econometric version of the conventional test, shows the degree of this bias.

Table 5 shows the estimation results when the dependent variable is food consumption. Both the conventional test and the SAR models cannot reject the FRSH because the coefficient on income is not significant. However, the co-movement of consumption is not perfect in all cases because the coefficient is significantly different from 1. The point estimate changes from the conventional test and the SAR model. The spatial lag term, which corresponds to the village-level average consumption, decreases from 0.916 to 0.721, and the coefficient on income increases from 0.0187 to 0.0212. These differences result from the bias in the conventional test. Once the spatial error term is introduced (Column 5 to 7), the qualitative results change drastically. Income has a significantly positive effect on food consumption and strongly rejects the FRSH. Furthermore, the spatial error term is significant in models with the inverse distance and kinship matrices, suggesting that ignoring the spatial correlation in unobservables leads to the wrong results.

Table 6 shows the results of the same specifications when the dependent variable is non-food consumption. All of the results reject the FRSH, because the coefficient on income is significantly different from zero. Similar to the food consumption case, the point estimate of income changes from the conventional test to the SAR with the block-based matrix. The spatial correlation in the error term is significant in Column 6. However, it is not significant in the SAC with the block-based and kinship matrices, which rather support the SAR model.

4.2. Handling Measurement Error

One possible concern in the results of Tables 5 and 6 is measurement error in the income variable. The measurement error, which is uncorrelated with the error term, causes attenuation bias in the regression coefficient. To address this issue, using an instrument correlated with true income but uncorrelated with the measurement error is necessary (Ravallion and Chaudhuri 1997; Kinnan 2012). This study uses the irrigation access dummy as the excluded instrument. As previously mentioned, there is variation in the timing of irrigation access among blocks. It is possible to assume that the portion of the income change explained by improved irrigation access is not correlated with the measurement error. This study employs a two-step procedure for the estimation. The first-stage model is estimated by regressing the income level on the irrigation access dummy and the individual fixed effects. The first-stage F test for the excluded instrument strongly rejects the null hypothesis that the coefficient is zero (F =17.46). Using the predicted values from this estimation, $\widehat{income}$, the previous specifications are re-estimated as the second stage[7].

Table 7 shows the two-step estimation results for food consumption. Except for the conventional test, all specifications reject the FRSH because the coefficient on income is significantly positive. Furthermore, the magnitude of coefficients is larger in the two-step estimation than in Table 5, confirming the existence of the attenuation bias. The spatial error term is significant in the SAC for both the inverse distance and the kinship matrices. Thus, omitting this term can cause problems in the FRSH tests.

Table 8 shows the results for non-food consumption. The coefficients on income become larger than those in Table 6, also confirming the attenuation bias, and the FRSH is rejected. The spatial lag term in the SAR with the inverse matrix is not significant, which rather supports the autarky situation. However, the SAC is superior to the SAR model because the spatial error is significant in Column 5. Regarding the kinship weight matrix, the SAC model supports autarky, but the spatial error term is insignificant.

4.3. Quantifying the Diffusion of Income Shocks

Using the results of the two-step estimation in Tables 7 and 8, the direct and indirect effects of an income shock can be estimated. Table 9 summarizes these effects for each specification. The last column shows the ratio of the indirect effect to the total one. For

[7] Since the two-step estimation of the SAC model with the block-based matrix does not converge for both food and non-food consumption, they are not reported in the tables.

food consumption, the indirect effect is larger for the block-based and inverse matrices than for the kinship one. This implies that income shocks diffuse better in spatial network than in a social one. Regarding non-food consumption, the indirect effect is insignificant in the SAR model with the inverse distance matrix and in the SAC one with the kinship matrix. This is because the spatial lag term is insignificant for these specifications in Table 8. Although the contrast is less clear than in the food consumption case, spatial networks also play an important role for diffusing income shocks to smooth non-food consumption.

Because these direct and indirect effects summarize the feedback effect of an income shock, investigating each element of the feedback effect matrix $S(W) = (I_n - \beta W)^{-1} I_n \gamma$ is also useful. Figures 3 and 4 show the relationship between the spatial distance and the elements of $S(W)$ in the SAC specifications using the inverse distance matrix for food consumption and non-food consumption, respectively. Although the results of the kernel-weighted local polynomial regression show a very flat and small-magnitude relationship, there are peaks at approximately 7 and 24 km. These non-linear relationships imply that there is a trade-off between the scope and effectiveness of risk sharing (e.g., Fafchamps and Gubert 2007). Although spatial distance increases transaction costs, it also reduces the possibility of facing covariate shocks. Therefore, the degree of risk sharing is a mixture of these positive and negative features.

4.4. Robustness Check

As a robustness check, the same specifications are re-estimated after dropping households with no kin from the sample. For these households, the spatial lag variable (Wc_t) is zero in the previous estimation because the entries in the corresponding row are all zero. This treatment might cause bias in the results with the kinship matrix. Table 10 shows the re-estimation results employing a two-step procedure, and Table 11 shows the direct and indirect effect using the results in Table 10. As shown in these tables, the qualitative results are virtually unchanged, which supports the robustness of the previous findings.

5. Conclusion

By employing spatial panel econometric models, this study extends the empirical tests of the FRSH to incorporate spatial and social network effects. This approach enables us to quantify the diffusion of income shocks in both spatial and social networks and to compare the effect of these networks. In addition, the conventional test can be regarded as a special case of a spatial econometric model, which implies an estimation bias in the conventional test.

The results after controlling for the attenuation bias of the income variable reject the FRSH in most cases. The point estimate changes from the conventional test to the spatial econometric model, confirming the bias in the conventional test. The results also show the existence of the spatially correlated unobservables, which are neglected in previous studies. These findings strongly support the effectiveness of the spatial econometric approach to the risk-sharing analysis.

The estimated direct and indirect effects show that income shocks are diffused in each network. Furthermore, the diffusion of income shocks in the spatial networks is larger than that in the social networks, especially for food consumption. This result suggests that consumption smoothing within spatial networks works better than that within social networks, implying that the reduction of transaction costs by living close together has a larger effect than facilitating transfers through the kinship network does. Therefore, mitigating individual risks by introducing formal insurance programs has a strong externality to boost welfare of neighboring households through a spatial risk-sharing mechanism.

Appendix: CRRA Specification

Another standard specification of the conventional test employs a CRRA utility function. In this case, the empirical test model is used to regress the log of consumption and income instead of these variables in level form, that is,

$$\log(c_{it}) = \beta\overline{\log(c_t)} + \gamma\log(y_{it}) + \eta_i + \varepsilon_{it}$$

One problem of this specification is that logarithms cannot be defined for negative values. As shown in Table 3, the reported income is negative for 7.4% of the samples because of large input costs in agriculture. Because the logarithm of these negative income cases cannot be defined, they are replaced with the value 1 before taking the log. In order to handle the bias arising from this treatment, a dummy variable that identifies these negative income cases is also included in the estimation.

Tables A1 and A2 show the estimation results for food and non-food consumption, respectively. The coefficient on income is significantly positive, which strongly rejects the FRSH. The spatial error term is significant when the weight is an inverse distance or kinship matrix. The spatial lag term is larger for the block-based and inverse distance matrices than for the kinship one, implying that households' consumption is better connected in spatial networks than in social ones. Table A3 summarizes the direct and indirect effects. Similar to the CARA specifications, the indirect effect is larger for the block-based and inverse distance matrices, implying that income shocks diffuse better in spatial networks than in social ones.

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Table 1: Summary of Expected Results

	Coefficient		Direct effect	Indirect effect
Hypothesis	Spatial lag	Income		
Full risk sharing	1	0	0	0
Partial risk sharing	+	+	+	+
No risk sharing (Autarky)	0	+*	+*	0

Note: In the case of autarky, the coefficient on income is identical to the direct effect.

Table 2: Irrigation Accessibility in Each Block

Year	2001		2002		2007		
Season	Maha	Yala	Maha	Yala	Maha	Yala	Sample Size
Survey round	1& 2	3	4	5	6	7	(total 171)
Sevanagala Irrigated	X	X	X	X	X	X	20
Sevanagala Rainfed							8
Kiriibbanwewa	X	X	X	X	X	X	16
Sooriyawewa	X	X	X	X	X	X	31
Mayurapura				X	X	X	82
Tissapura						X	14

Figure 1: Location of Sample Households

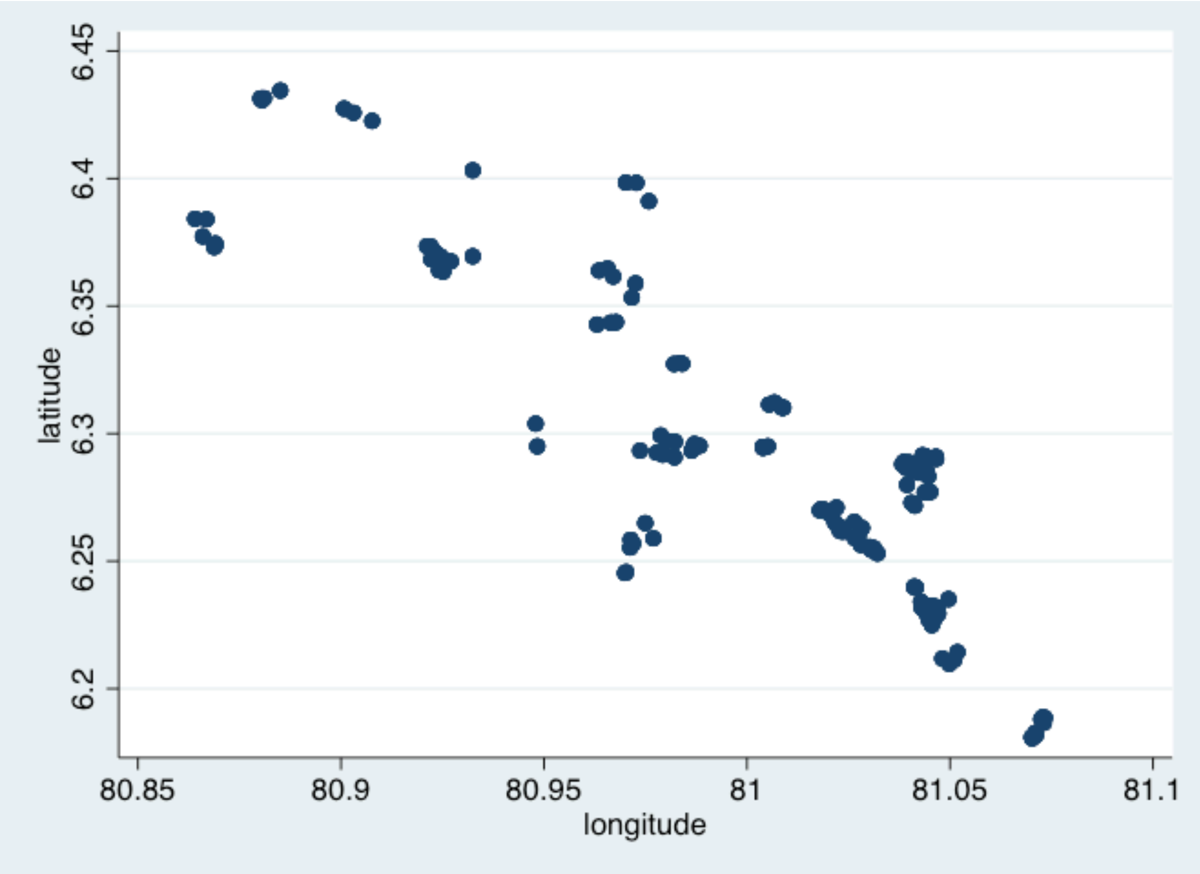

Figure 2: Graph of Kinship Network

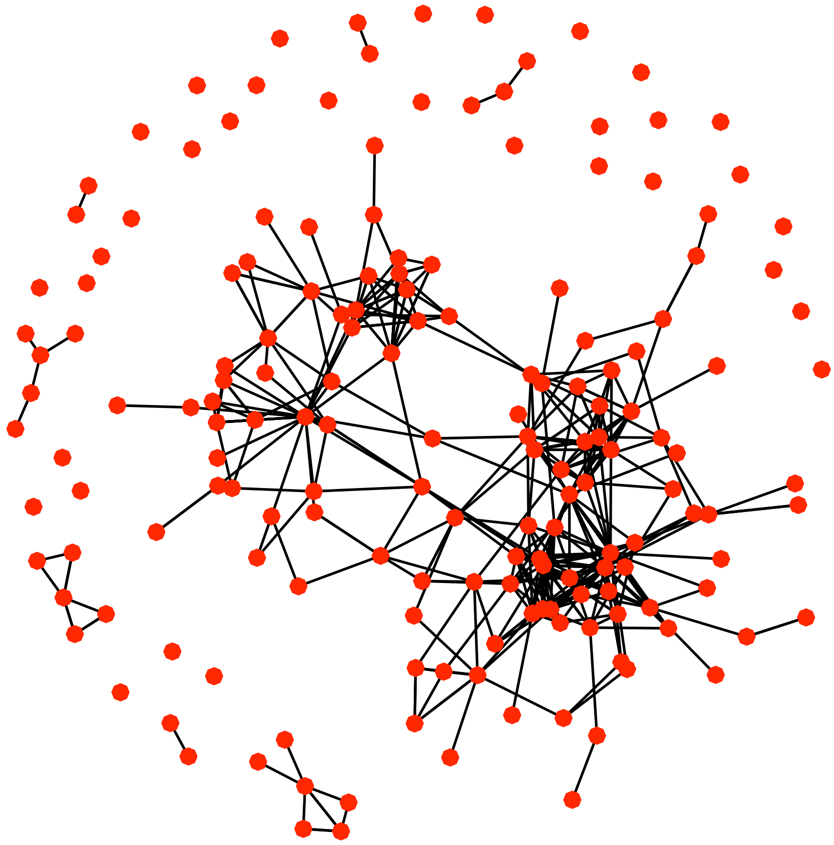

Table 3: Descriptive Statistics

Variable	Unit	Obs	Mean	Std. Dev.
Adult equivalent scale		1026	4.437914	1.572229
Food consumption	Rs.	1026	31488.09	16067.27
Non-food consumption	Rs.	1026	20003.52	33612.68
Income	Rs.	1026	35070.84	50461.43
Negative income dummy	Binary	1026	0.0740741	0.2620191
Irrigation access dummy	Binary	1026	0.5516569	0.4975669

Note: Both consumption and income are in real terms and based on 2005 Sri Lanka Rupees.

Table 4: Moran's *I* of Consumption and Income Shocks by Cropping Seasons

	Season					
Weight Matrix	Maha 2001	Yala 2001	Maha 2002	Yala 2002	Maha 2007	Yala 2007
Income change						
Block based	0.008	0.009	-0.004	0.131***	0.031**	0.028**
	(0.734)	(0.84)	(0.151)	(7.17)	(1.982)	(1.763)
Inverse distance	0.036*	0.015	-0.01	0.078***	0.01	0.033*
	(1.487)	(0.802)	(0.197)	(2.947)	(0.576)	(1.364)
Kinship	-0.068	0.054	0.001	0.086	0.055	0.005
	(0.881)	(0.889)	(0.14)	(1.276)	(0.864)	(0.155)
Food consumption						
Block based	0.029**	-0.022	-0.015	0.004	-0.006	0.032**
	(1.851)	(0.847)	(0.499)	(0.538)	(0.018)	(2.01)
Inverse distance	0.029	-0.013	-0.009	-0.018	0.031*	0.04*
	(1.224)	(0.266)	(0.882)	(0.437)	(1.314)	(1.625)
Kinship	0.023	0.054	-0.07	0.118**	-0.055	0.152**
	(0.399)	(0.838)	(0.882)	(1.724)	(-0.684)	(2.207)
Non-food consumption						
Block based	-0.017	0.017	-0.024	-0.011	-0.021	-0.014
	(0.662)	(1.261)	(0.981)	(0.259)	(0.989)	(0.474)
Inverse distance	0.042**	0.049**	0.076***	-0.014	-0.068***	-0.038
	(1.839)	(2.009)	(2.99)	(0.274)	(2.796)	(1.194)
Kinship	0.337	0.071	0.027	-0.051	-0.043	0.122**
	(0.655)	(1.115)	(0.473)	(0.631)	(0.654)	(1.888)

The absolute values of the z-statistics are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Model Estimation Results for Food Consumption (One-step)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	Conventional	SAR	SAR	SAR	SAC	SAC	SAC
Weight Matrix	NA	Block	Inv. Dist.	Kinship	Block	Inv. Dist.	Kinship
Average consumption	0.916***						
	(0.0718)						
Spatial lag		0.721***	0.701***	0.385***	0.838***	0.901***	0.607***
		(0.0332)	(0.0434)	(0.0513)	(0.0665)	(0.0244)	(0.0572)
Income	0.0187	0.0212	0.0242	0.0276	0.0203***	0.0164**	0.0245***
	(0.0143)	(0.0149)	(0.0153)	(0.0174)	(0.00751)	(0.00703)	(0.00854)
Spatial error					-0.696	-0.797***	-0.321***
					(0.635)	(0.108)	(0.0864)
Observations	1,026	855	855	855	855	855	855
R-squared	0.266	0.033	0.049	0.026	0.029	0.081	0.022
Number of households	171	171	171	171	171	171	171

The dependent variable is the adult-equivalent food consumption. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Model Estimation Results for Non-Food Consumption (One-step)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	Conventional	SAR	SAR	SAR	SAC	SAC	SAC
Weight Matrix	NA	Block	Inv. Dist.	Kinship	Block	Inv. Dist.	Kinship
Average consumption	0.570***						
	(0.0897)						
Spatial lag		0.351***	0.150**	0.184***	0.565***	0.865***	0.0976
		(0.0492)	(0.0686)	(0.0654)	(0.196)	(0.0363)	(0.117)
Income	0.0648*	0.0694*	0.0744*	0.0731*	0.0685***	0.0486***	0.0736***
	(0.0378)	(0.0382)	(0.0392)	(0.0389)	(0.0205)	(0.0167)	(0.0215)
Spatial error					-0.504	-1.171***	0.110
					(0.655)	(0.0792)	(0.118)
Observations	1,026	855	855	855	855	855	855
R-squared	0.043	0.035	0.033	0.032	0.036	0.040	0.032
Number of households	171	171	171	171	171	171	171

The dependent variable is adult equivalent non-food consumption. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Model Estimation Results for Food Consumption (Two-step)

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Conventional	SAR	SAR	SAR	SAC	SAC
Weight Matrix	NA	Block	Inv. Dist.	Kinship	Inv. Dist.	Kinship
Average consumption	0.875***					
	(0.0912)					
Spatial lag		0.644***	0.601***	0.228***	0.855***	0.380***
		(0.0449)	(0.0504)	(0.0532)	(0.0348)	(0.0885)
Income (predicted)	0.0855	0.243***	0.273***	0.564***	0.110***	0.479***
	(0.0987)	(0.0848)	(0.0843)	(0.0738)	(0.0398)	(0.0717)
Spatial error					-0.766***	-0.192*
					(0.113)	(0.107)
Observations	1,026	855	855	855	855	855
R-squared	0.293	0.090	0.114	0.066	0.186	0.063
Number of households	171	171	171	171	171	171

The dependent variable is adult-equivalent food consumption. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Model Estimation Results for Non-food Consumption (Two-step)

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Conventional	SAR	SAR	SAR	SAC	SAC
Weight Matrix	NA	Block	Inv. Dist.	Kinship	Inv. Dist.	Kinship
Average consumption	0.352***					
	(0.0858)					
Spatial lag		0.193***	0.0368	0.114**	0.836***	0.0752
		(0.0435)	(0.0488)	(0.0579)	(0.0451)	(0.105)
Income (predicted)	0.511***	0.636***	0.761***	0.722***	0.154**	0.746***
	(0.168)	(0.156)	(0.151)	(0.134)	(0.0727)	(0.160)
Spatial error					-1.151***	0.0514
					(0.0841)	(0.107)
Observations	1,026	855	855	855	855	855
R-squared	0.041	0.046	0.044	0.045	0.067	0.045
Number of households	171	171	171	171	171	171

The dependent variable is adult-equivalent non-food consumption. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Direct and Indirect Effect of the Income Variable (Two-step)

	Direct	Indirect	Total	Indirect / Total
Food consumption				
Model: SAR				
Block	0.252***	0.435***	0.687***	63.32%
	(0.0738)	(0.125)	(0.186)	
Inv. Dist.	0.282***	0.409***	0.690***	59.28%
	(0.0734)	(0.115)	(0.172)	
Kinship	0.566***	0.116***	0.682***	17.01%
	(0.0626)	(0.0366)	(0.0778)	
Model: SAC				
Inv. Dist.	0.122***	0.663***	0.785***	84.46%
	(0.0363)	(0.204)	(0.221)	
Kinship	0.487***	0.198***	0.685***	28.91%
	(0.0588)	(0.0602)	(0.0687)	
Non-food consumption				
Model: SAR				
Block	0.635***	0.152***	0.786***	19.34%
	(0.132)	(0.0431)	(0.150)	
Inv. Dist.	0.759***	0.0318	0.791***	4.02%
	(0.128)	(0.0428)	(0.126)	
Kinship	0.722***	0.0691*	0.791***	8.74%
	(0.114)	(0.0417)	(0.132)	
Model: SAC				
Inv. Dist.	0.170**	0.838**	1.008**	83.13%
	(0.0664)	(0.420)	(0.452)	
Kinship	0.745***	0.0496	0.794***	6.25%
	(0.135)	(0.0699)	(0.135)	

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 3: Spatial Distance and Income Shock Diffusion (Food Consumption)

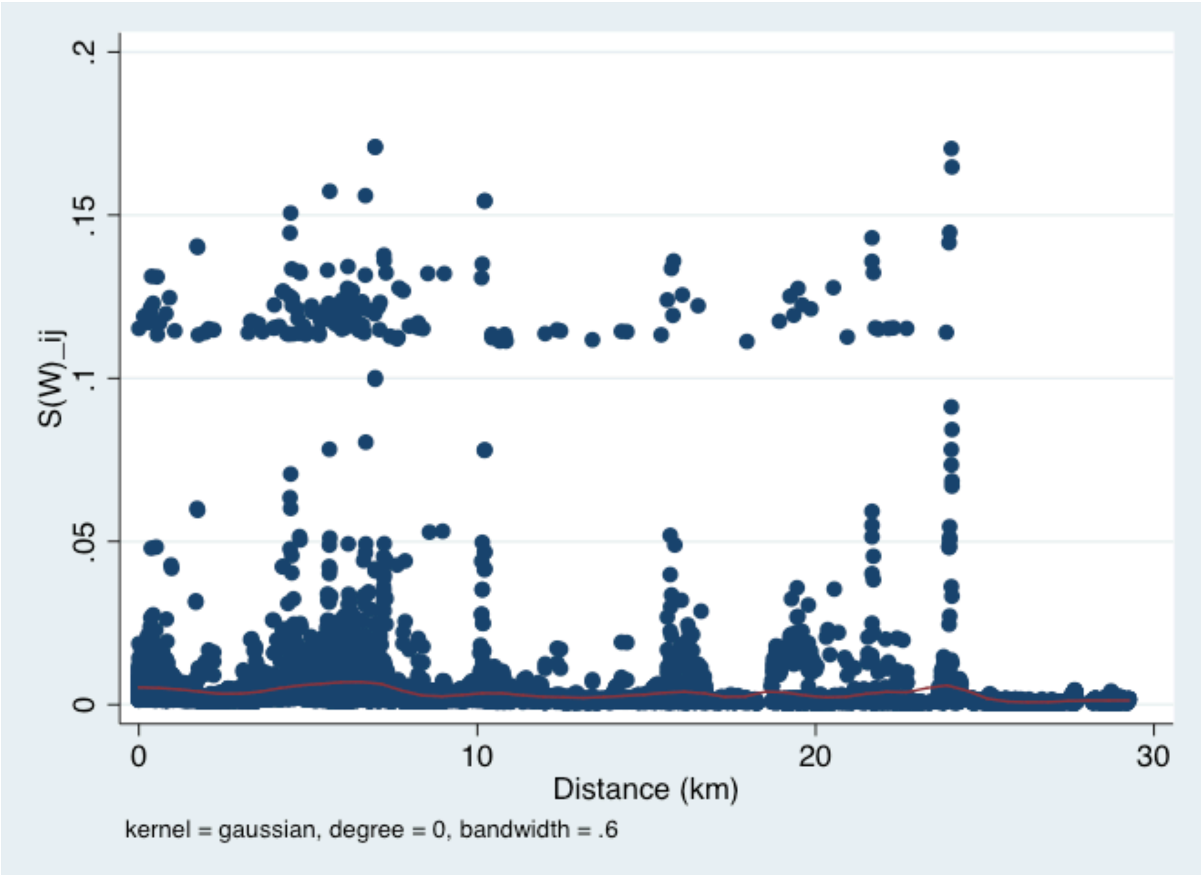

Figure 4: Spatial Distance and Income Shock Diffusion (Non-food Consumption)

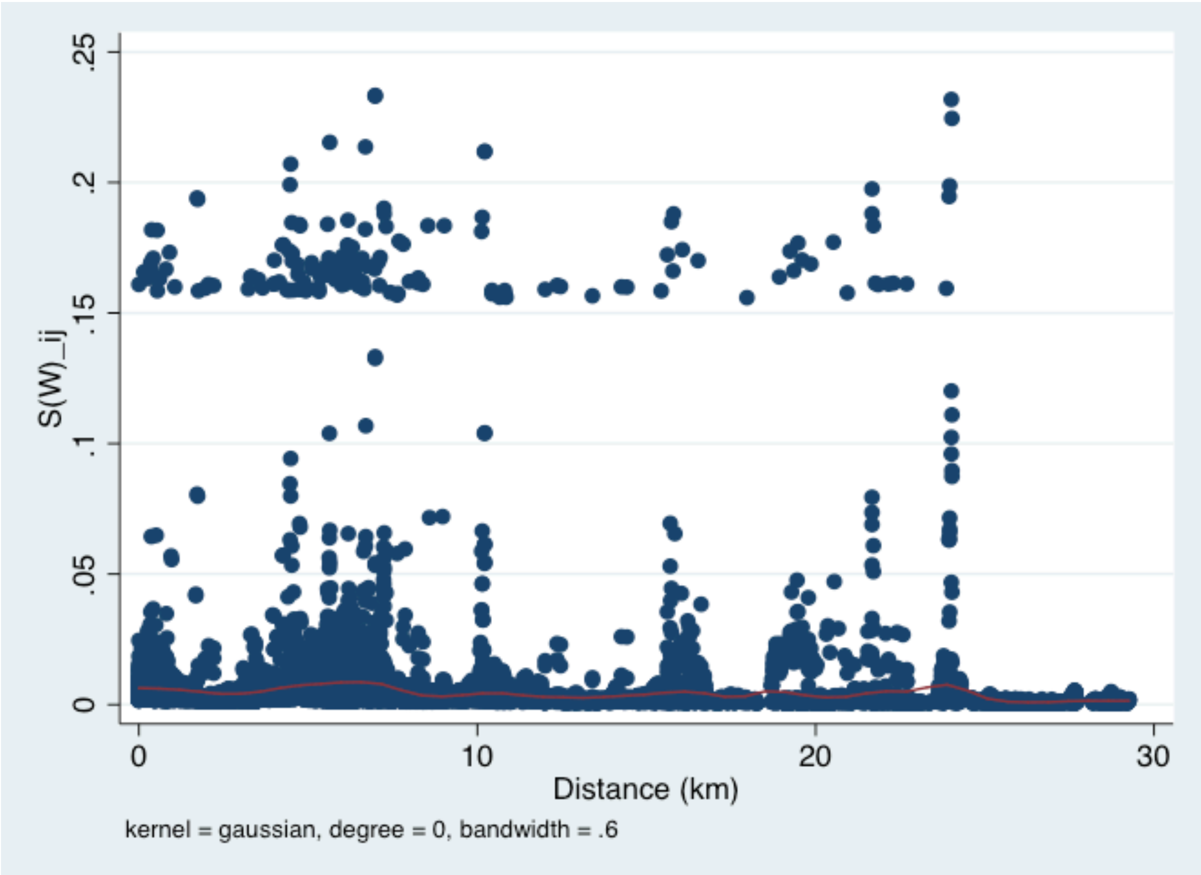

Table 10: Robustness Check for the Kinship Matrix (Two-step)

	(1)	(2)	(3)	(4)
	SAR	SAC	SAR	SAC
Weight Matrix	Kinship	Kinship	Kinship	Kinship
VARIABLES	Food	Food	Non-food	Non-food
Spatial lag	0.203***	0.380***	0.0717*	0.0533
	(0.0522)	(0.0902)	(0.0374)	(0.103)
Income (predicted)	0.576***	0.460***	0.720***	0.733***
	(0.0808)	(0.0770)	(0.158)	(0.178)
Spatial error		-0.218**		0.0259
		(0.110)		(0.104)
Observations	570	570	570	570
R-squared	0.069	0.068	0.042	0.042
Number of households	114	114	114	114

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness Check

	Direct	Indirect	Total	Indirect / Total
Food consumption				
Model: SAR				
Kinship	0.579***	0.148***	0.727***	20.36%
	(0.0686)	(0.0508)	(0.0926)	
Model: SAC				
Kinship	0.474***	0.279***	0.753***	37.05%
	(0.0619)	(0.0854)	(0.0857)	
Non-food consumption				
Model: SAR				
Kinship	0.719***	0.0581*	0.777***	7.60%
	(0.134)	(0.0350)	(0.147)	
Model: SAC				
Kinship	0.732***	0.0498	0.781***	5.96%
	(0.151)	(0.0917)	(0.155)	

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A1: CRRA Specification for Food Consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	Conventional	SAR	SAR	SAR	SAC	SAC	SAC
Weight Matrix	NA	Block	Inv. Dist.	Kinship	Block	Inv. Dist.	Kinship
Average consumption	0.902***						
	(0.0620)						
Spatial lag		0.717***	0.693***	0.355***	0.858***	0.896***	0.623***
		(0.0326)	(0.0400)	(0.0465)	(0.0491)	(0.0239)	(0.0503)
Income	0.0410***	0.0460***	0.0466***	0.0565***	0.0356***	0.0319***	0.0451***
	(0.0156)	(0.0157)	(0.0150)	(0.0172)	(0.0123)	(0.0102)	(0.0126)
Negative income dummy	0.392***	0.457***	0.465***	0.607***	0.377***	0.324***	0.494***
	(0.142)	(0.142)	(0.137)	(0.157)	(0.113)	(0.0978)	(0.119)
Spatial error					-0.994	-0.828***	-0.384***
					(0.630)	(0.104)	(0.0752)
Observations	1,026	855	855	855	855	855	855
R-squared	0.310	0.076	0.112	0.019	0.071	0.184	0.003
Number of households	171	171	171	171	171	171	171

The dependent variable is the adult-equivalent food consumption. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2: CRRA Specification for Non-food Consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	Conventional	SAR	SAR	SAR	SAC	SAC	SAC
Weight Matrix	NA	Block	Inv. Dist.	Kinship	Block	Inv. Dist.	Kinship
Average consumption	0.831***						
	(0.0830)						
Spatial lag		0.590***	0.495***	0.252***	0.532**	0.826***	0.538***
		(0.0478)	(0.0573)	(0.0508)	(0.240)	(0.0371)	(0.0636)
Income	0.0833**	0.0985***	0.107***	0.118***	0.0985***	0.0910***	0.106***
	(0.0375)	(0.0377)	(0.0386)	(0.0402)	(0.0333)	(0.0281)	(0.0321)
Negative income dummy	0.695**	0.866**	0.959***	1.087***	0.858***	0.827***	1.011***
	(0.338)	(0.343)	(0.355)	(0.370)	(0.320)	(0.267)	(0.301)
Spatial error					0.129	-0.843***	-0.364***
					(0.451)	(0.112)	(0.0855)
Observations	1,026	855	855	855	855	855	855
R-squared	0.185	0.081	0.090	0.048	0.076	0.109	0.016
Number of households	171	171	171	171	171	171	171

The dependent variable is the adult-equivalent non-food consumption. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: CRRA Specification of Direct and Indirect Effects

	Direct	Indirect	Total	Indirect / Total
Food consumption				
Model: SAR				
Block	0.0489***	0.116***	0.165***	70.30%
	(0.0142)	(0.0387)	(0.0516)	
Inv. Dist.	0.0491***	0.106***	0.155***	68.39%
	(0.0135)	(0.0370)	(0.0487)	
Kinship	0.0571***	0.0208***	0.0779***	26.70%
	(0.0148)	(0.00712)	(0.0210)	
Model: SAC				
Block	0.0428***	0.234**	0.277**	84.48%
	(0.0112)	(0.106)	(0.111)	
Inv. Dist.	0.0366***	0.287***	0.323***	88.85%
	(0.00992)	(0.107)	(0.114)	
Kinship	0.0479***	0.0457***	0.0936***	48.82%
	(0.0113)	(0.0134)	(0.0233)	
Non-food consumption				
Model: SAR				
Block	0.101***	0.143**	0.244***	58.61%
	(0.0331)	(0.0572)	(0.0871)	
Inv. Dist.	0.109***	0.106**	0.216***	49.07%
	(0.0336)	(0.0435)	(0.0732)	
Kinship	0.118***	0.0273**	0.145***	18.83%
	(0.0344)	(0.0113)	(0.0435)	
Model: SAC				
Block	0.111	0.417	0.528	78.98%
	(0.263)	(7.153)	(7.415)	
Inv. Dist.	0.100***	0.450***	0.550***	81.82%
	(0.0262)	(0.167)	(0.185)	
Kinship	0.111***	0.0793***	0.190***	41.74%
	(0.0283)	(0.0273)	(0.0517)	

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1