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Risk-sharing networks and insurance against illness

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Abstract

Most risk-sharing tests on developing country data are conducted at the level of the village; generally, the full risk-sharing hypothesis is rejected. This paper uses detailed data on all insurance networks within a village in Tanzania; networks are not clustered but largely overlapping. We test whether full risk-sharing occurs within these networks. While village level full-insurance cannot be rejected for food consumption, we find evidence consistent with at least partial insurance of non-food consumption via networks.

JEL classification: O12; O15; D12
Keywords: Full insurance hypothesis; Risk-sharing; Networks; Health shocks

1. Introduction

Households living in developing countries are often faced with unpredictable income streams and expenditure needs. A growing body of literature investigates the strategies that households employ to smooth consumption in the face of shocks (for surveys see Alderman and Paxson, 1994; Morduch, 1995, 1999; Deaton, 1997). A particular strand of this literature has focused on the overall efficacy of these strategies by concentrating on the smoothness of consumption over time or in the cross-section through testing the full-risk sharing hypothesis (Deaton, 1992; Townsend, 1994; Ligon, 1998; Ligon et al., 2002; Gertler and Gruber, 2002). In this paper, we build on this literature to test risk-sharing using panel data from rural Tanzania, but focus on risk-sharing within networks rather than at the village level. We derive testable predictions for full risk-sharing across networks, when networks within the village are overlapping. To test this, we

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use detailed data from a full census of all insurance networks within the village and investigate the impact of illness shocks on outcomes.

The level at which one should test risk-sharing has received relatively little attention. For developing countries, most researchers have taken the village as the unit of analysis. There are two reasons for this. First, it is argued that information and enforcement problems are likely to be small between the members of a village and this creates a favourable environment for co-operation. Secondly, the sampling strategy and questionnaires used to collect household data typically allow the identification of clusters or villages for analysis, but it is often difficult to find any other sensible unit of analysis. Still, it is acknowledged that there might be a better basis to test the full insurance hypothesis (e.g. Townsend, 1994, p. 541).

There are some exceptions however. For the United States, using the Panel Study of Income Dynamics (PSID) data, Altonji et al. (1992) were able to use information on child "split-offs". These are children of parents that were in the initial sample, who, upon forming their own households, were included in the panel too (also their parents remain in the panel). Linking the data of parents and children allows these authors to specify a test of whether "extended families" are altruistically linked, by testing whether consumption decisions are based on a common budget constraint, i.e. individual consumption within the family is independent of the distribution of income between the households. Grimard (1997) studies risk-sharing among ethnic groups in Côte d'Ivoire. Ligon (2001) finds suggestive evidence for the existence of two distinct risk-sharing networks (divided along wealth lines) in one of the International Crops Research Institute of the Semi-Arid Tropics (ICRISAT) villages. Rosenzweig (1988) uses data on the family structure of the households in the ICRISAT sample to investigate extent of transfers in responses to idiosyncratic income shocks, and finds that households with more family links outside the household have transfers that are more responsive to income shocks. Dercon and Krishnan (2000) test risk-sharing within nuclear households in Ethiopia, and find that although generally risk-sharing could not be rejected, full insurance against illness shocks does not take place within poor households in the South of the country.

The a priori grounds for using the village as a basis for full insurance are not always clear, especially when risk-sharing institutions are important. First, some households may form more or less formalised groups (burial societies, women's groups, labour sharing groups, etc.). Some (but certainly not all) of these groups may have an insurance element in them and generally (but not always) they comprise only a subsection of the households of the village.

Secondly, consider an economy with heterogeneous agents. There may be heterogeneity with respect to information flows, norms, trust, correlation of income streams, etc. In that case, when a household forms its network, it will not consider all other households to be equally suited as insurance partners (e.g. Rosenzweig and Stark, 1989). For example, in many societies a single village is spread over a substantial area and information flows are, ceteris paribus, better between close neighbours than between villagers living, say, 1 km apart. Also, households involved in similar activities are likely to have better information concerning each other's income. These and countless other factors make the smoothness of information flows, and thus the ease with which an insurance link can be forged and used, unequally distributed across all dyads[1] in the same village.

Similarly, even within the same village households belong to different clans, castes, families, religions, etc. These 'institutions' may help impose norms and trust among their members. Ceteris

[1] In network analysis, a dyad is a pair of households. When we say 'across all dyads', we mean across all possible combinations of two households in the village.

paribus, this creates an incentive to form links within one's group. Finally, if villagers are heterogeneous with respect to their income generating activities, then the potential gains of co-operation may differ greatly across all dyads. Two households engaged in different activities may have weakly correlated income streams and may thus be better insurance partners (if we abstract from any informational concerns). Heterogeneity across dyads may cause a particular household to prefer to enter into an insurance arrangement with only a subsection of his fellow villagers and not with all of them. This does, of course, not exclude the possibility of risk-sharing at village level.

Even so, researchers have offered other compelling evidence (both empirical and theoretical) that insurance groups do not necessarily form at village level. Murgai et al. (2002) argue that there are increasing costs to group size. As the network becomes larger the task of co-ordinating transfers, gathering information and enforcing contracts becomes more difficult. In such an environment, full insurance at village level becomes an extreme case. They back this argument up with an empirical study of water exchanges along irrigation canals in Pakistan. Genicot and Ray (2003) show that one does not even have to impose increasing costs to have bounded group size. They consider a non-cooperative risk-sharing model, which is robust not only to single-person deviations, but also to subgroup deviations. They show that introducing this (quite natural) assumption is sufficient to put bounds on the size of the network.

In an empirical study of the rural Philippines, Fafchamps and Lund (2003) find that mutual insurance takes place through networks of relatives and friends and not at village level. Their analysis gives insights in which coping strategies are used in response to which shocks. It can also evaluate the efficiency of each coping strategy individually, but it does not yield a satisfactory answer to the question of whether all insurance mechanisms put together serve to smooth consumption. Unlike them, we will not make any inferences about the efficiency of any specific coping strategy, but we will provide a test of whether all strategies put together smooth consumption. In doing so, we will be able to consider that networks do not necessarily lie at village level.

But even if the size of the insurance groups is inherently bound to be a number smaller than the number of households in the village, this still does not exclude full insurance at village level. More specifically, it can be shown that if every household belongs to a network and all these networks overlap with each other (have some common members), then full insurance within the confines of the separate networks necessarily implies Pareto-efficiency at village-level. In Section 2, we extend the standard full insurance model to allow for potentially overlapping networks.

Next, in Section 3, we use a data set from rural Tanzania to give a broad overview of how people reacted with different coping strategies to the two major shocks of the past 10 years. In Section 4, we use the same survey to formally test the full insurance hypothesis. Controlling for aggregate network resources and aggregate village resources, we investigate whether households are able to smooth consumption, including when faced with severe health shocks. We pay close attention to a number of econometric problems, in particular that illness may be predictable, that illness may have persistent effects and that illness may affect preferences. We also address the problem that networks may be endogenous in our regressions.

2. Model and econometric specification

It is helpful to consider two cases of 'networks'. The first case is an isolated network in the sense that the members cannot enter into an insurance arrangement with anyone outside the network. While the empirical assessment whether such networks provide risk-sharing is interesting, the theoretical model involved is effectively the same as the standard village-level network risk-sharing test. The second case is more interesting: there are multiple overlapping networks so that at least one person is a member of at least two networks. To develop this case, consider a village which consists of two networks. Say, network 1 has N_1 members and network 2 has N_2 members. Everyone in the village is member of exactly one network, except household k, which is member of both networks.

First, let us consider what full risk-sharing were to imply in network 1. Let each household i in network 1 get a Pareto-share ω_i, with $\omega_i>0$, $\forall$ i and $\sum\omega_i=1$. This Pareto-share reflects the relative weight of the household in the allocation within the network, for example through some initial bargaining process or via a social planner. Pareto-efficient allocation of risk then amounts to maximising a weighted sum of household utilities subject to a network resource constraint. Let C_{it} be the consumption of household i at time t and λ_t the Lagrange multiplier associated with the aggregate network resource constraint at time t. Assuming utility functions with $U'>0$ and $U'<0$, then some standard manipulation of the first order condition yields that for any two members i and j:

$$\frac{U'(C_{it})}{U'(C_{jt})}=\frac{\omega_j}{\omega_i} \tag{1}$$

which shows that the marginal utility of each household's consumption reflects its Pareto weight in the program. Assuming constant relative risk aversion (governed by ρ), let instantaneous utility be represented by

$$U(C_{it})=(1-\rho)^{-1}\theta_{it}n_{it}\left(\frac{C_{it}}{n_{it}}\right)^{1-\rho} \tag{2}$$

in which θ_{it} accounts for intertemporal needs of the household, which are not already captured by the household size, n_{it}. Using (1) and (2) and taking logarithms gives:

$$\ln\left(\frac{C_{it}}{n_{it}}\right)=\ln\left(\frac{C_{jt}}{n_{jt}}\right)-\rho^{-1}\left(\ln\theta_{jt}-\ln\theta_{it}\right)-\rho^{-1}\left(\ln\omega_j-\ln\omega_i\right) \tag{3}$$

This equation holds across all the $N-1$ dyads that household i belongs to. Adding up these $N-1$ equations yields (Bardhan and Udry, 1999), and taking differences results in:

$$\Delta\ln\left(\frac{C_{it}}{n_{it}}\right)=\Delta\bar{C}_{\mathrm{NW}_1t}-\rho^{-1}\left(\frac{1}{N_1-1}\sum_{j=1}^{N_1-1}\Delta\ln\theta_{jt}-\Delta\ln\theta_{it}\right) \tag{4}$$

where $\bar{C}_{\mathrm{NW}_1t}=\frac{1}{N_1-1}\sum_{j=1}^{N_1-1}\ln\frac{C_{jt}}{n_{jt}}$ or average (logarithm of) network consumption at time t.

This implies the standard result under the full insurance risk-sharing hypothesis that household resources that are uncorrelated with shifts in preferences should not affect consumption growth once aggregate resources are controlled for. Numerous studies have made use of Eq. (4) to test the full insurance hypothesis at village level. A similar condition can be derived for the other network. However, if there is an overlapping member k, then for this household, both (5) and (6) will hold.

$$\Delta\ln\left(\frac{C_{kt}}{n_{kt}}\right)=\Delta\bar{C}_{\mathrm{NW}_1t}-\rho^{-1}\left(\frac{1}{N_1-1}\sum_{j=1}^{N_1-1}\Delta\ln\theta_{jt}-\Delta\ln\theta_{kt}\right) \tag{5}$$

and

$$\Delta \ln\left(\frac{C_{kt}}{n_{kt}}\right) = \Delta \bar{C}_{\mathrm{NW}_2 t} - \rho^{-1}\left(\frac{1}{N_2-1}\sum_{j=1}^{N_2-1}\Delta\ln\theta_{jt} - \Delta\ln\theta_{kt}\right) \tag{6}$$

which means that

$$\Delta \bar{C}_{\mathrm{NW}_1 t} = \Delta \bar{C}_{\mathrm{NW}_2 t} + \rho^{-1}\left(\frac{1}{N-1_1}\sum_{j=1}^{N_1-1}\Delta\ln\theta_{jt} - \frac{1}{N_2-1}\sum_{j=1}^{N_2-1}\Delta\ln\theta_{jt}\right). \tag{7}$$

If both networks operate Pareto-efficiently and they contain at least one common household, then the change in their average network consumption will be equal, up to taste-shifters. This means that the growth in household consumption will be equal for all households within and across both networks (up to taste-shifters) and village-wide full insurance holds. Even though both networks only pool risk within the confines of their own group, risk will be allocated as if it is pooled across all N_1+N_2-1 households in the village.

2.1. Regression specification

Next, we specify an empirical test for risk-sharing across the village and networks, and include a means of determining whether or not households are fully insured against severe health shocks. Health shocks are particularly suitable for studying the implications of the full insurance model as they are often large, idiosyncratic and unpredictable.[2] Other shocks are likely to be more predictable. As Morduch (1995) points out, if an income shock can be predicted beforehand, then households may have side-stepped the problem by engaging in costly ex-ante smoothing strategies (e.g. diversifying crops, plots and activities). Although health is less vulnerable to this critique than income, we will nevertheless take this possibility into account and purge health shocks of their expected components. Health shocks typically imply an impact on labour supply, while also squeezing resources to be spent on standard consumption items to pay for health expenses.

Say we have some measure of health, denoted by H_{it}, then ΔH_{it} can be interpreted as a health shock. If household i shares risk with only a subsection of the village, then we can construct a set of i's network members, say N_i, and write the cardinality of this set as $\#N_i$. We can then write a standard risk-sharing testing equation, augmented for networks as:

$$\Delta \ln\left(\frac{C_{it}}{n_{it}}\right) = \alpha\Delta H_{it} + \beta\Delta\left[\frac{\sum_{j\in N_i}\frac{C_{jt}}{n_{jt}}}{\#\mathrm{N_i}}\right] + \gamma D_t + \delta\Delta V_{it} + \varepsilon_{it}. \tag{8}$$

A full set of time dummies, D_t, controls for village level terms in (8), including variations of aggregate village resources and possibly village level ‘taste shifters’ (Ravallion and Chaudhuri, 1997).[3] V_{it} represent time-varying demographic characteristics of the household and they are assumed to capture the changes in household-level taste shifters included in (8). ΔH_{it} is introduced as an over-specification of the econometric model implied by (8), with $\alpha=0$ if full risk-

[2] Of course, there are also small health shock and even common health shocks (e.g. epidemics), but if the data are rich enough it is possible to separate these.

[3] We study only one village. When several villages are included in the regression, village-time dummies are appropriate.

sharing is taking place. For example, Gertler and Gruber (2002) estimate (7) without controlling for network effects and find that Indonesian households are unable to smooth 30% of the income loss from severe illnesses.

From (8), it follows that under Pareto-efficient risk-sharing at the village level (possibly through overlapping Pareto-efficient networks), β cannot be estimated because aggregate network consumption would then be perfectly collinear with aggregate village consumption. It is more complicated to pin down the predictions in the case of the lack of perfect risk-sharing, but overall, a significant coefficient β would point to the relevance of networks.

There is a well-developed theoretical literature for the case of imperfect risk-sharing for isolated groups or villages (e.g. due to enforcement or information constraints): they would imply partial and not complete smoothing (Ligon, 1998; Ligon et al., 2002). In the case of non-overlapping networks, this would mean significant network effects, even after controlling for village level effects.

In the case of overlapping networks, this would not apply straightforwardly, and existing theory models offer relatively little guidance. One possible avenue would be to consider that different groups do not pay out for all income shocks in the same way. For example, some groups exclude certain shocks. Or they sometimes do not pay out, for example, because it would undermine the continuation of the group (linked to enforcement constraints). Or they do not compensate for losses incurred by a member who was made to provide a net transfer into another group of which she was a member, after a shock occurred to one of the members in that group.

One implication is that this effectively implies that the overlap of individuals across groups is not resulting in perfect co-movement: i.e. the fact that person k is a member of two groups does not mean that both groups' consumption will move in lock-step, unless all members are overlapping and/or are fully insured against all shocks in other ways. This means (7) does not hold, even though some insurance of households via networks is still taking place. In this case, even in a village of overlapping networks, a shock to the consumption of your network partners is not transmitted to all their network partners and throughout the village. Changes in network resources will affect your consumption, even after controlling for village level resources.

The test for risk-sharing formulated above is defined in terms of one composite consumption good. Following Gertler and Gruber (2002), Morduch (2001) and others, we will test risk-sharing not just for total consumption, but also for food and non-food consumption separately. The main argument is that different types of consumption may have a differential sensitivity to shocks and also, they may suffer from different types of measurement error, affecting the ability of our tests to identify any failure in risk-sharing or network effects. It is worth noting that the nature of the test is unaffected when using commodity groups, compared to using total consumption. To see this, consider two commodities, food, C_{it}^{f} and non-food, C_{it}^{nf}. Using the same set-up as before, the only change is that we now have two first order conditions — one for each commodity, but otherwise, the basic model is unchanged. Defining U_{f} as the marginal utility from increasing food consumption, (1) can be rewritten as:

$$\frac{U_{\mathrm{f}}(C_{it}^{\mathrm{f}}, C_{it}^{\mathrm{nf}})}{U_{\mathrm{f}}(C_{jt}^{\mathrm{f}}, C_{jt}^{\mathrm{nf}})} = \frac{\omega_j}{\omega_i} \tag{9}$$

while a similar condition can be written for non-food consumption. The standard result is maintained: the relative marginal utilities of two households will remain constant over time. A specification defined in terms of the commodity group, but otherwise identical to (7), can also be obtained from (9). A sufficient condition is that the marginal utility for one commodity is independent of consumption of the other commodity, but additivity of the utility function across commodities is a strong assumption. However, even if there is non-separability between the commodity groups, it follows directly from (9) that under perfect risk-sharing, individual resources should still not matter, but only network or community resources (Cochrane, 1991, p. 965). This implies that (8), defined in commodity groups, remains the basis for a valid test of risk-sharing and the role of networks. Note, however, that since income effects may be different across goods, the impact on individual consumption of shocks to network and (if perfect risk-sharing does not hold) to individual resources may well be different across goods. In particular, the income elasticity of the demand for food is likely to be lower than for non-food.

2.2. Econometric problems

Some econometric problems have to be taken into account when estimating Eq. (8). The first set relates to the use of illness as an idiosyncratic shock. If illness in period t is predictable, households might already have made some ex ante provisions for it in period $t-1$ (e.g. increased savings). Our results would then overestimate the ability of households to smooth truly unpredictable shocks. To check robustness, we tackle this problem by subtracting the predictable part of H_{it} from the measured H_{it}, as in Dercon and Krishnan (2000). The predictable part of H_{it} is measured through a fixed effects regression of H_{it} on household characteristics, consumption in period $t-1$ and time dummies. Another issue is that illness may have permanent effects on the income process. This would present problems for our test: it may be that the immediate impact of the shock is insured but in subsequent periods, consumption would suffer after all, due to the loss of income earning ability. One implication is that a history of illness shocks would matter to understand the full impact on the path of consumption. To test for these persistent effects, we introduce lagged illness shocks, and if there are persistent effects, they should show up in the test.

A third problem is that the interpretation of our results strongly depends on the assumption that the utility function is separable in consumption and health. If this is not the case, then even perfectly insured households will change their consumption path after an illness shock. In that case, ΔH_{it} will be correlated with the error term, and its coefficient biased.[4] A further problem is that consumption shocks may be the cause of health shocks and not the other way round. In the discussion of the regression results we will touch on these last two issues again and provide evidence that indicates that the results are neither driven by non-separability, nor by health feed-backs.

Another problem is that network formation is endogenous. The direction of the bias of β is not a priori clear. On the one hand, concerns about trust and smooth information flows might make households choose network partners with correlated income streams (e.g. close neighbours or households with the similar activities). On the other hand, network partners might be selected *because* they are expected to have negatively correlated income streams.[5] In both cases, the factors that determine networks may directly influence household consumption. Therefore, we instrument changes in average network consumption, using changes in demographic characteristics of network members during the survey period for a given network and remittance

[4] Dubois and Ligon (2003) shed some light on the relevance of the preference shifts in response to illness, by exploiting individual food expenditure data. They estimate the effect of illness on individual demand of specific members within a household, controlling for the effects of illness on total household expenditures. They find a significant effect, but it is rather small, especially for calorie and protein intake.

[5] Grimard (1997) points to exactly this type of trade-off, which households in Côte d'Ivoire have to make when choosing their insurance partners. Household living close by are easily monitored, but have correlated risk, while households living far away are difficult to monitor, but have uncorrelated risk.

flows to network members from outside the network as identifying instruments. Especially the latter appears a reasonable instrument, since transfers from outside the network to a household's network partners can only influence consumption of the household via the network.[6] By using IV-estimation, we may also be able to address measurement error problems in the consumption of network members (on this, see also Ravallion and Chaudhuri, 1997).

3. Shocks experienced in the past 10 years

The data come from a household survey administered in Nyakatoke, a typical Haya village in the Bukoba Rural District of the Kagera region of Tanzania. From February to December 2000 all the 120 households in the village were visited 5 times at regular intervals. We did not take a sample of households, but interviewed all the households living in the village. The total recall periods of most survey questions cover exactly one year (split into 5 rounds). First, household interviews were administered to all household heads. These served to collect data on assets, consumption, education, health and demographic movements. A few days later, individual interviews were administered to all 220 adult individuals of the village. Questions concerning gifts, loans, labour allocation, income, etc. were then put to the respondents.

Before turning to the full insurance test in the next section, we present self-reported data on how households have coped with the major shocks of the past 10 years. Apart from giving a broad overview of shocks and coping strategies, we want to make three points, which motivate the econometric analysis in the next section. First, illness is most frequently identified as an important shock. This helps substantiate our claim that in the econometric analysis we are dealing with a shock that matters. Secondly, at least based on the descriptive statistics, households seem to be far from a full insurance situation, also when it comes to health shocks: consumption appears to be substantially affected by illness. Thirdly, risk-sharing via transfers is the most important coping strategy to deal with the consequences of health shocks. This also indicates that a correct specification of the insurance network is important for any inferences about the Pareto-efficiency of risk allocation. If households do not rely on risk sharing then the specification of the network does not matter.

In the fifth and final round of the survey, we queried all adult individuals in the village for the two worst shocks their households had experienced in the past 10 years. It was stressed that we meant shocks that had a negative *economic* impact on the household.[7] The 207 respondents listed a total of 296 shocks — younger respondents typically had less than two shocks to report. The shocks were not pre-coded, but written in the questionnaire as the respondents described them. Later on we aggregated them into 7 groups. Table 1 summarises the frequency with which these shocks were reported and how they affected the daily consumption of the household. As can be expected, households were least affected by ceremonies. Lumpy expenditures score surprisingly high.[8] Households appear to cut back on consumption to invest in a house, a bicycle or education.

[6] Nevertheless, the level of transfers from outside the network is an equilibrium outcome, determined by the demand and supply of transfers. Ideally, one would like a measure of the supply of transfers and remittances, and not the equilibrium of supply and demand, since the demand would largely be determined within the network, and in that sense is the demand for remittances as an instrument not necessarily superior to characteristics of the households in the network. Still, this need not imply a direct effect from remittances to network partners of a household to consumption of the household.

[7] The framing of the question in Swahili was as follows: "katika miaka kumi iliyopita, kuna madhara gani ambayo yameathiri kaya yako kiuchumi".

[8] Strictly speaking these are not shocks, but choice variables.

Table 1
Which were the two worst shocks that affected your household in the past 10 years?

Shock	Description	No. of times reported		% of these cases that reported having been forced to cut back daily consumption		
		N	%	Not at all	Moderately	Severely
Death/funeral	On the one hand, the financial costs associated with the funeral ceremony. This can be huge as Haya funerals are big events with several dozens of guests who have to be catered for several days. On the other hand the loss in income, if the deceased was an income generator. Also included here, are cases where respondents mentioned a long period of sickness resulting in death as a single shock.	51	17	8	31	60
Ceremonies	60% of these cases are weddings, 17% are ceremonies related to the birth of a child and others are related to religious or traditional Haya festivities like baptism, kwihukya, kuzilima and kujali.	42	14	32	53	16
Sickness	All costs associated with being ill. On the one hand medical expenditures (e.g. hospital bills, consultation fees, buying medicine, transportation to the hospital). On the other hand income loss through reduced labour supply (directly of the sick person him/herself and/or indirectly because of others being absent or busy accompanying/nursing him or her).	82	28	8	36	56
Lumpy expenditures	45% of these cases refer to the building of a house. For the construction of a house one needs costly inputs like skilled and unskilled labour, nails, ropes, poles etc.… and possibly also corrugated iron sheets. 26% mentioned expenditures on education and the other cases were people buying farms, land, bicycles etc.…	31	10	17	37	47
Crime and court cases	Individuals who had livestock, farm produce or durables stolen, who were victims of physical violence, who were suspected of crimes, or were taken to court or to prison.	40	14	15	28	56
Shock in income generating activities	In 12 cases bad agricultural prices or weather shocks (often El Niño) are mentioned. Job loss and shocks in off-farm activities are mentioned in 13 cases. It would have been better to disaggregate further into common and idiosyncratic shocks here, but there are too few observations to do this.	25	8	0	36	64
Others	All other shocks on which we had too few data points to justify them being put in separate categories. 8 respondents mentioned the burning down of their house. Generally a fire will leave nothing standing of the structure of the house and destroy all belongings inside (including clothes, cash, etc.…). Three respondents mentioned absconded husbands.	25	8	4	30	65
Total		296	100	12	36	52

Source: Nyakatoke Household Survey.

Table 2
Coping strategies used in the past 10 years (in response to the 2 worst shocks that have affected household in the past 10 years)

	Number of times reported			
	Counting only those who rated this response as very important		Counting all entries	
	N	% [a]	*N*	% [a]
Risk-sharing	126	43	224	76
Private gifts	86	29	177	60
Private loans	40	14	76	26
Private labour transfers	18	6	106	36
Community organisations	40	14	84	28
Savings (drawing on cash reserves)	122	41	197	67
Sale of assets	110	37	166	56
Stocks	54	18	95	32
Livestock	37	13	53	18
Butura [b]	19	6	29	10
Durables	15	5	29	10
Land	3	1	5	2
Earning extra income	52	18	95	32
Casual labour	27	9	47	16
Other incomes	27	9	54	18
Others	3	1	7	2
Taking children from school	0	0	6	2
Moneylenders	2	1	2	1
Help from the government or NGOs	1	0	2	1

Source: Nyakatoke Household Survey.
[a] The denominator is the total number of shocks that were mentioned (296).
[b] Butura is a Haya practise in which the farmer gives up the right to some premature crop – usually coffee – in return for cash; when the crop is ready for harvesting, the buyer of the butura can claim it.

Unless one is willing to assume that all the reported shocks were common (which is extremely unlikely, with the clear exception of the 12 respondents who mentioned bad prices and adverse weather shocks).[9] Only 12% of the shocks are reported to have no effect on daily consumption (and many of these are in the category ‘ceremonies’). About half of the shocks were reported to have affected daily consumption severely. Illness is the most frequently mentioned shock and, as Table 1 shows, 92% of these respondents say that this specific spell of illness had at least some effect on their daily consumption.

Next, we queried respondents on the coping strategies they used to face these shocks. Table 2 summarises the responses. Risk-sharing was most frequently mentioned. We see that gifts are the most popular form of risk-sharing. Loans and help through groups follow at some distance. Loans are always very flexible, zero-interest arrangements between parties who know each other well. Guarantors or collateral are hardly ever used. Local groups usually help with transfers in kind, cash and of labour. The groups of Nyakatoke are described in detail in De Weerdt (2000). Just under half of the respondents who reported to have used their social capital got help in the form of

[9] None of the seven categories of shocks is concentrated in a particular year. There is, however, a tendency to report what happened recently. This is probably due to the fact that respondents have a more vivid recollection of these shocks, and that we inquired about shocks that occurred since the formation of their household (which is less than 10 years ago for younger respondents).

Table 3
Responses to the two major shocks of the past 10 years (percentage of shocks for which the response was considering to be 'very important')

	% of cases which reported to have used the following coping strategy in response to the shock specified (only those considered 'very important')				
	Risk-sharing	Savings in cash	Sale of assets	Earning extra income	Others
Death	57	33	39	10	4
Ceremonies	52	74	17	17	0
Sickness	50	37	44	13	0
Lumpy expenditures	32	61	45	13	0
Crime and court cases	33	28	40	15	0
Shock in income generating activities	12	32	32	44	0
Others	32	24	36	32	0
Total	43	41	37	18	0

Source: Nyakatoke Household Survey.
The denominator is the number of times the shock was mentioned.

labour. Typically, this is helping out at funerals or ceremonies, helping to carry a sick person to hospital, etc. Table 2 shows that labour help is very frequently offered, but it does not score high in terms of perceived importance.

Savings (in the form of cash) and the sale of assets are the next most important coping strategies. Cash comes in very irregularly; the largest chunk is from the annual coffee harvest. There are no banking services available, so everyone stores at least some cash at home. By far the most popular asset to sell is stocks (maize, beans, etc.). Livestock scores considerably lower, and durables and butura lower still.[10] Land is seldom sold. Because of market imperfections, once a fertile, well situated plot is lost, it is difficult to buy back a similar plot after recovering from the shock and it would certainly have to happen at a much higher price than the household had (in an emergency) sold at before.

Taking on extra income earning activities is an oft observed response to shocks.[11] Casual labour is the most popular and involves doing farm work for others for around TSh 200 ($0.25) for 4 h of hard work. Qualitative evidence suggests that casual labour is a poor man's coping strategy. Its use may be limited by seasonality in the labour market and by the very nature of the shock (e.g. death, illness or imprisonment of an important labour force in the household). Other extra income generating activities–all of them very labour intensive–include trading fish and other goods, cutting grasses (used for mulching and as floor covering in the house), porting, additional brewing and distilling of rubisi (the local banana beer), selling snacks at local markets and increased efforts to sell agricultural produce.

Table 3 links the data on coping strategies with those on shocks. Risk-sharing is most important in the case of a funeral, a ceremony or a health shock. It seems to fail, however, when it comes to shocks in income generating activities.[12] As expected, savings are most important for foreseeable events like lumpy expenditures and ceremonies.

[10] Butura is a Haya practise in which rights to a premature crop, usually coffee, are sold, as in a forward sale.
[11] Kochar (1995), in an analysis of the ICRISAT data for households in central India, stresses the importance of increased labour supply as a response to shocks.
[12] This is suggestive evidence for imperfect risk-sharing linked to information constraints as in Ligon (1998).

4. Data and regression results

These self-reported data suggest that households may well be vulnerable to shocks, including health, although some shocks may well be insured by risk-sharing arrangements. In this section, we present a formal test, investigating whether the consequences of these shocks are shared across households in networks and the village, based on the model discussed in Section 2. Mutual insurance is cited as the most important strategy to cope with health shocks, while households identify specific network partners. This implies that it is crucial to specify the consumption smoothing test at the correct network level.

Non-food consumption is measured in between rounds, while the recall period for food consumption is 1 week. From the pilot interviews it became apparent that respondents had great difficulties in recalling the exact quantities of staple food they had consumed in the past week. Because it was such a tedious and extremely disliked exercise, we decided to adopt a different approach. Every meal has one staple and this is either rice, cooking bananas, or *myaka*, which is the Haya term for staples like cassava, yams, sweet potatoes, cocoyams, etc. This is a natural way for the villagers themselves to classify meals and thus it was not problematic to recall how many meals of each type they had eaten in the past week. These three different kinds of staples had clear price differences, with rice being most expensive, followed by bananas and followed by *myaka*. Carefully collected qualitative evidence suggests that there is no malnutrition in the village in terms of carbohydrates. Therefore, we attached an age–sex weighted value to each type of staple, under the assumption that everyone had their fill. All other food consumption was measured in exact quantities and values.

This approach will be able to pick up the impact of shocks if households switch between staples in the face of shocks, e.g. eat more *myaka* and less cooking bananas. However, a problem of this approach may be that, in the face of a health shock, households may substitute their protein-rich food, like meat and fish, for staples. In this case our data would show the decrease in protein-rich foods, but not the increase in the consumption of staples. Thus, if anything, the data would exaggerate the decrease in food consumption and underestimate the degree of consumption smoothing. Note that this may bias coefficients on health shocks *against* finding risk-sharing. As will be seen below, this effectively strengthens our results for food consumption.

We used a relatively narrow definition of non-food consumption, but we present sensitivity analysis on the impact of broader definitions of non-food consumption on our results. The most narrow definition includes spending on kerosene, batteries, soap, other toiletries, basic educational spending and rent. The broader definitions used also include clothing, tobacco, chewing coffee, drinks outside the household, repairs and durables expenditure (although health expenditures are excluded). The key hypothesis is that the broader the definition, the more items are included the preferences for which may have changed in response to health shocks, and thereby affecting our test.[13]

Table 4 gives the mean and standard deviation of the food, non-food and total consumption across the five survey rounds used in the basic test. Values are expressed in Tanzanian Shillings per adult equivalent per week. There are about 800 Tanzanian Shillings to a dollar and the equivalence scales we used are based on Dercon and Krishnan (1998). Note that Nyakatoke is an extremely poor village. Average consumption per household is only about $8.00 per week, which

[13] An alternative definition of food consumption, including alcohol and any drinks bought outside the household, was tested as well, since alcohol or soft drinks may be another commodity consumed less due to a preference shift linked to illness, but no significantly different results to those reported in the text could be found.

Table 4
Mean and standard deviation of non-deflated food, non-food and total consumption across the 5 survey rounds (in TSh per week per adult equivalent)

	Food consumption	Non-food consumption	Total consumption
Round 1	1066 (500)	467 (832)	1533 (1094)
Round 2	1065 (460)	273 (303)	1338 (672)
Round 3	1146 (528)	541 (485)	1687 (836)
Round 4	1221 (498)	263 (744)	1484 (939)
Round 5	1242 (417)	186 (204)	1428 (498)
Total	1146 (486)	348 (586)	1494 (841)
N	566	566	566

Source: Nyakatoke Household Survey.
In each cell the top number is the mean and the bottom one (between brackets) the standard deviation.

works out to be just under $2.00 per adult equivalent unit. The average food-share in consumption is about 77%. The data are not deflated, which means that they are difficult to compare across rounds, as prices tend to have a high degree of seasonality. Furthermore, the data may well reflect important seasonality in preferences and consequently expenditures. Price and preference changes across rounds will be controlled for in the regression results by including time (round) dummies.

The data on health shocks come from a section in the household questionnaire where we requested respondents to make a list of any new or ongoing illnesses in the household. Next, and for each household member that had been ill, we asked whether the illness had an adverse effect on the income earning capacity of the household (not at all, moderately or severely). From these responses, we constructed a dummy variable which is 1 when the household reports to have incurred a severe loss in farm or off-farm income generating activities due to illness. We define a health shock as the first difference of this dummy. The first column of Table 5 shows that 11% of the cases in the pooled data set have incurred a health shock.[14] The survey question on which the health dummy is based was meant to capture shocks through reduced labour supply. The median days lost due to being unable to work is 14 days per serious health shock (mean of 17). Three quarters of these cases are adult members of the household, 25% are children below 18 and 5% are members older than 70.[15] Even then, we cannot exclude that part of consumption impact of the illness shock will not result from the reduction in labour supply, but rather from the acute need for cash for medical expenditures. Indeed, the average medical expenditures for severe health shocks are TSh 4825, about 14 times the weekly non-food consumption per adult equivalent (using the narrow definition of non-food consumption).

Before turning to the regression results, we present a simple, univariate analysis of the relation between consumption and illness. The second row of Table 5 shows that households with health shocks have an average consumption downfall of 4.3%, while those who do not experience any shocks (i.e. their index remains constant, or they go from sick to healthy) experience a rise in consumption of 4.5%. The two last columns show that this drop in consumption is entirely caused by a significant drop in non-food consumption.

[14] This means, on average, 11% in each round. Illness episodes are not concentrated in a particular round, so they can be seen as idiosyncratic shocks (not epidemics).

[15] Some of them might not be important for the supply of labour of the household. Still, household labour supply can be reduced because a household member has to nurse the patient. Indeed 80% of the children that fall into this category were admitted to hospital and thus required intensive nursing.

Table 5
Impact of health shocks on consumption: average consumption change between rounds

Health shock	% of pooled sample	Number of days reported unable to work (median)	Δln total consumption	Δln food consumption	Δln non-food consumption
No	89	0	0.045	0.053	−0.009
Yes	11	14	−0.043	0.039	−0.235
Total	100	0	0.036	0.051	−0.033

Source: Nyakatoke Household Survey.
N=433; because we look at first differences, we 'lose' one round of observations. The definition of food, non-food and total consumption used is a 'narrow' definition, excluding durables, alcohol and chewing coffee.

In the empirical test, we need to control for network consumption, without making any a priori assumption about the network partners of each household. To do this, we make use of a survey question in which we asked respondents to list everyone they depend on for help and/or everyone who depends on them for help. Respondents mentioned a total of 1126 network partners, of which two-thirds live inside the village. Since 120 households were interviewed, this means that each household typically listed about 10 network partners on average. Because we took a full sample of the village, we can link all the network members who live inside the village to their respective questionnaires. Table 6 summarizes the links between households in the village and shows that these networks are strongly overlapping (for more details, see De Weerdt, 2004). Individuals mentioned between 1 and 11 intra-village network partners in their interviews. Aggregated at household level this gives an average of 6.3. The degree of interconnectedness and overlap in the network is illustrated well by measuring the geodesic distance between each pair of households in the village. A geodesic distance of 1 means that the two households are directly connected. A geodesic distance of 2 means that they are both connected to a common network partner, i.e. it takes two steps to get from one household to the other. Note that all households are connected within 5 steps of each other and the majority are only 2 to 3 steps apart. This also implies that there are no isolated 'sub-networks' of households within the village that have no connections between each other.

These network data are used to calculate the average consumption of the network of each household (excluding the household itself) and include it as a regressor to control for network

Table 6
Characteristics of the Insurance Network in Nyakatoke

No. of links reported between individuals	Mean	3.5
	Median	3
	Minimum	1
	Maximum	11
No. of links reported between households	Mean	6.3
	Median	5
	Minimum	2
	Maximum	22
Geodesic distance (minimum number of steps necessary to connect two households) − absolute frequencies in sample	1	490
	2	1996
	3	2900
	4	1275
	5	360

Source: Nyakatoke Household Survey.

Table 7
First stage regression: explaining changes in the log of network consumption per adult (N=387)

	Δln total consumption		Δln food consumption		Δln non-food consumption	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Δln Boys in network (up to 5)	−0.155	0.05	−0.180	0.02	−0.210	0.16
Δln Boys in network (from 5 to 15)	0.026	0.71	0.010	0.87	0.082	0.51
Δln Male adults in network (15 plus)	−0.124	0.00	−0.085	0.02	−0.238	0.00
Δln Girls in network (up to 5)	−0.089	0.32	−0.107	0.20	−0.151	0.36
Δln Girls in network (from 5 to 15)	−0.100	0.09	−0.093	0.09	0.060	0.58
Δln Female adults in network (15 plus)	−0.151	0.01	−0.029	0.56	−0.072	0.45
Δln Livestock values owned in network	0.000	0.73	0.000	0.47	0.000	0.91
Δln Remittances from outside network	0.005	0.43	−0.027	−0.58	0.028	0.01
R^2	0.22		0.11		0.21	
p-value joint significance F-test of excluded instruments, F(8,368)	0.00		0.01		0.01	

Source: Nyakatoke Household Survey.
First stage results from 2SLS estimates. Only identifying regressors (excluded instruments) reported. Time dummies, individual illness shocks and household characteristics included but not reported; illness shocks never significant. All left-hand side variables are changes in logarithms of characteristics (plus 1) in per adult terms. We use the narrow definition of different parts of consumption. All regressions include time dummies. The consumption concept (food, non-food or total) for the network partners is always the same as that for own consumption and expressed in natural logarithms.

consumption (the second RHS term in Eq. (8)). As a robustness test, results are also presented for an alternative specification of the network, which takes flows of resources across nodes into account. Here we define the network as all households who are at most 2 steps away from each other (geodesic distance equal to 1 or 2). Thus, compared to the basic specification, the network partners of one's network partners are also included.

Network formation may be endogenous and this could bias β, since unobservable factors influencing network consumption may also influence consumption directly. By using fixed effects (first differences), we purge the regression of any time-invariant factors which determine both network formation and consumption levels. Note that this means that we effectively control for a wide variety of characteristics that may determine why networks may have been formed before the survey period in this particular way to start with, including relative wealth levels, trust, ability or risk aversion. We also use a number of time-varying instruments. First, we use *changes* in demographic characteristics and in the value of livestock wealth as further controls. Still, we can expect some unobserved factors determining both the change in network consumption and the change in own consumption if network partners are chosen according to, for example, profession and geographical distance. We use the change in the mean value of remittances received by members of the network from outside the network: these remittances are likely to only affect the consumption of the household via the network and not directly. Finally, round-specific time dummies control for prices or seasonality.

Given their importance for our results, Table 7 reports these regressions explaining (changes in) direct network consumption (excluding the household).[16] These regressions are the first stage regressions in the IV-version of our test for risk-sharing via networks. Changes in male adults are statistically significant in all regressions while changes in other demographic characteristics also

[16] The definitions used for food, non-food and total consumption mirror those used in the 'basic', narrow specification of the risk-sharing test.

Table 8
Testing risk-sharing and network effects

	OLS-estimates (n=387)			IV-regression (network consumption endogenous) (n=387)			IV-regression (network consumption endogenous) and unexpected health shocks (n=278)		
	Δln food cons (1)	Δln non-food cons (2)	Δln total cons (3)	Δln food cons (4)	Δln non-food cons (5)	Δln total cons (6)	Δln food cons (7)	Δln non-food cons (8)	Δln total cons (9)
Health shock	−0.022	−0.040	−0.031	−0.024	−0.001	−0.027	−0.048	−0.078	−0.073
	(0.50)	(0.57)	(0.39)	(0.46)	(0.97)	(0.44)	(0.22)	(0.38)	(0.09)
Δln network consumption	−0.003	−0.013	0.090	−0.306	1.201	0.387	−0.194	0.792	0.137
	(0.97)	(0.92)	(0.31)	(0.52)	(0.03)	(0.29)	(0.60)	(0.03)	(0.63)
p-value for joint significance *F*	0.05	0.00	0.00	0.08	0.01	0.00	0.02	0.00	0.00
p-value for Hansen *J*-statistic				0.33	0.32	0.07	0.41	0.51	0.20

LHS = changes in log consumption per adult (i.e. fixed effects within estimator). Robust standard errors. *P*-values in brackets.
Source: Nyakatoke Household Survey.
Estimated using 2SLS, with the first stage identifying instruments reported in Table 6. All regressions include the change in 6 demographic categories (males and females aged 0 to 5, 6 to 15 and 16+). We use the narrow definition of different parts of consumption. All regressions include time dummies. The consumption concept (food, non-food or total) for the network partners is always the same as that for own consumption and expressed in natural logarithms. Tests statistics reported include the *p*-value for the Hansen *J*-statistic.

matter in the food and total consumption regressions. Most relevant for our purposes, changes in remittances into the network are positive and significant at 1% in the non-food consumption regression. Since the latter is the 'best' instrument suitable for identification, this is encouraging at least for the non-food consumption regressions, and at same time this suggests that the results for food and total consumption may have to be interpreted with caution, since they rely only on changes in demographic characteristics over time to identify network consumption.

Next, we turn to the full insurance test (Table 8). Besides network consumption, the regression also included a number of controls for preference shifts, including changes in household demographics and time (round) dummies. Time dummies capture any village effects (including fluctuations in aggregate village resources and prices). We report three sets of results. In columns (1) to (3), we report the OLS (within) estimator for total, food and non-food consumption. Columns (4) to (6) give IV-regression treating network consumption as endogenous using changes in household demographics, livestock values and remittances from outside the network as identifying instruments. In (7) to (9), we report the same IV-regression, but using unpredicted health shocks as our measure of health shocks, using lagged values of characteristics and consumption to purge illness from any predictable parts. Given that another round is 'lost' to derive predicted illness, the sample is smaller.

The results on the impact of health shocks are not systematically the same. They generally suggest that we cannot reject the hypothesis that health shocks are insured: the impact is negative but not significant. But health shocks are significant at 9% for unexpected health shocks and total consumption, implying overall, consumption declines by 7.3% if a serious health shock occurs, in line with the qualitative evidence.

The most interesting result for our purposes relates to the effect of network consumption. There is no significant impact of network consumption on food in any of the regressions, with or without IV. Combined with the health shocks findings, this would suggest that households manage to insure food consumption at least conditional on village level resources.[17] However, for non-food consumption, this result does not hold: here we find that without instrumenting network non-food consumption is not significant (column (2)), but it becomes positive and significant at 3% when instrumented. This effect holds when using unpredicted health shocks. Taken together, this is evidence that networks matter for insuring shocks, but also that endogeneity is relevant. The direction of the change of the network coefficient between the uninstrumented and instrumented coefficients is consistent with networks formation that takes into account a desired tendency for negatively correlated income changes, sensible from a pure insurance point of view.[18] Since the a priori clearest identifying variable (remittances from outside the network) is only significant in the non-food

[17] As usual in this type of test, one cannot distinguish whether they manage to insure themselves via transfers, self-insurance or other means. Even if transfers were responsible, the test cannot distinguish whether networks and within network transfers are responsible for this — in any case, the test statistics do not rule this out. We know that all regression specifications control for aggregate village resources through time dummies and we know that all networks in the village overlap with each other. In Section 2 we showed that when all networks overlap, full insurance at the network level would imply full insurance at the village level. In fact, village and network consumption changes should be indistinguishable, with measurement error providing the only reason why perfect collinearity may not occur. The insignificant network coefficients are consistent with this interpretation. The qualitative evidence discussed in Section 3 (Table 3) provides some evidence that both informal transfers and self-insurance may play a role.

[18] Note that the difference between instrumented and non-instrumented network consumption would also be consistent with a measurement error problem in the network consumption variable.

regressions, the results regarding food and total consumption may be related to problems with the first stage regressions.[19]

Overall this suggests that networks matter for risk-sharing for non-food consumption,[20] while the possibility of full insurance at the village level cannot be rejected for basic food consumption. How robust are these results? Given that non-food consumption gives the clearest results on the role of networks, we explore these results further. A number of potential problems with the interpretation of the results will be discussed in turn. They include non-separability of consumption and health shocks, persistent effects of these shocks, issues related to the appropriate definition of non-food consumption and the definition of the network. Table 9 gives a number of results, using a specification as in column (5) of Table 8 (i.e. endogenous network consumption with actual health shocks). First, it could be argued that illness shocks have persistent or even permanent effects. Then, simply identifying the shock when it appears, may not capture its full effect and thereby overstate the extent of smoothing or insurance obtained. If illness shocks have long-lasting effects, then lagged shocks should add explanatory power to understand contemporaneous changes in consumption; in any case, there should not be a recovery. The first column in Table 8 shows that we cannot find any evidence of persistent effects — the coefficient on lagged illness is not significant, while all the other coefficients are similar to before (i.e. network consumption matters). Secondly, the results may be driven by using a specific, possibly arbitrary definition of non-food consumption. Columns (2) and (3) show the impact of broadening this definition — first, including clothing and some consumables such as tobacco and chewing tobacco, and next, including durables as well. The impact of network consumption is again strongly significant for the broadest definition, although only significant at 15% in column (2). Interestingly, the impact of health shocks in column (2) is now strongly negative and significant — suggesting a drop of non-food consumption of 17.7% in case of a serious health shock, adding credence that health shocks are not fully insured and, in line with the qualitative evidence, that they cause consumption declines. It is possible that this result is driven by non-separability — health shocks causing a shift in preferences against certain non-food consumption items. Still, the fact that illness shocks are not significant for the broadest definition of non-food consumption, and the qualitative evidence would suggest that this is not necessarily the most plausible interpretation.[21]

In general, the evidence in Tables 8 and 9 points to the role of networks for smoothing non-food consumption. However, this is evidence based on a particular empirical definition of the relevant network. An alternative definition could include not just direct network partners but also the partners of the network partners. Introducing the consumption of the indirect network partners separately or together with direct network partners' consumption was not found to be significant

[19] The Hansen *J*-statistic is used to test the validity of these instruments. This is a test of the joint null hypothesis that the excluded instruments are valid instruments, i.e., uncorrelated with the error term and correctly excluded from the estimated equation. The test cannot be rejected for food and non-food consumption, but is problematic for the total consumption regressions, adding further credence to the possibility that endogeneity is causing the insignificance of network consumption in the total consumption regression.

[20] Given overlapping networks, this is not consistent with full insurance via networks, but rather with partial insurance.

[21] Non-separability and preference shifts linked to illness are unlikely to fundamentally drive the food consumption results either, since when using a broader definition, including alcohol and any drinks bought outside the household, the results were not affected: illness was not significantly affecting food consumption, even though these are items that may most plausibly be cut when ill. Furthermore, the fact that food consumption or the most narrow definition of non-food consumption does not appear to be affected by illness shocks seems to limit the possibility that reverse causality is causing any of the results as well, since illness is likely to be more closely affected by cutting back food or essential non-food consumption such as toiletries.

Table 9
Testing risk-sharing and network effects: robustness tests (fixed effects within estimator, robust standard errors)

	IV-regression. LHS = Δln non-food consumption, and network consumption endogenous. *P*-values in brackets				
	Persistence in health shocks (1)	Broader definition of non-food consumption (2)	Broadest definition of non-food consumption (3)	Broader network definition (4)	Broader and narrow network definition (5)
Health shock	−0.029 (0.77)	−0.177 (0.04)	−0.100 (0.35)	−0.027 (0.69)	−0.032 (0.66)
Lagged health shock	0.056 (0.52)				
Δln (close) network consumption	0.948 (0.02)	0.612 (0.15)	0.902 (0.03)		1.23 (0.03)
Δln network consumption (broader)				0.276 (0.67)	−0.861 (0.26)
p-value for joint significance *F*	0.02	0.000	0.000	0.00	0.00
p-value for Hansen *J*-statistic	0.91	0.46	0.82	0.04	0.22
N	288	387	387	387	387

Source: Nyakatoke Household Survey.
See Table 7 for full specification and controls. Persistence in health shocks column uses the specification as in column (5), Table 7, but including lagged health shocks. Similarly, the 'broader network' regressions uses an identical specification as in (5) but with a network definition including partners of network partners. The 'broader definition of non-food consumption' regressions use a definition based on the narrow definition but expanded to include in (2), clothing, chewing coffee and tobacco and in (3), the same plus durable expenditures as well.

(columns (4) and (5)). This suggests that direct network partners are most relevant for understanding risk-sharing.

5. Conclusion

This paper investigated the role of networks in insuring idiosyncratic shocks such as health shocks. We presented an extension of the standard framework for testing risk-sharing that takes into account overlapping networks. We used detailed panel data from a village in Tanzania with information on all self-reported insurance network links. For food consumption, we could not reject the hypothesis of full risk-sharing at the village level, but for non-food consumption we found evidence of insurance at the level of networks, rather than the village, as well as of the endogeneity of networks. We find less strong, but suggestive evidence that illness was not fully insured. The findings for the role of networks are robust to a number of problems related to the specification of the test, including the persistence of health shocks, different definitions for non-food consumption and networks, and the possibility of preference shifts linked to health shocks linked to non-separability between health and consumption.

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