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. We find that even within these smaller networks risk is not fully shared. In the event of a health shock, households reduce overall consumption: they cut back non-food consumption by roughly 30%, while protecting their food consumption.

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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 apply to smooth consumption in the face of shocks (for surveys see Alderman and Paxson, 1992; 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, Thomas and Worall, 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 use detailed data from a full census of all insurance networks within the village by looking at 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, Hayashi and Kotlikoff (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. 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 in poor households in the South of the country.

The a priori grounds for using the village as a basis for full insurance -especially when risk-sharing institutions are important- are not always clear. 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 kilometre 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 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

[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.

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 (2002) 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 (2002) 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 serious about the fact 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 set up a full insurance model, and from it we derive a regression equation. Under the full insurance risk-sharing hypothesis household resources that are uncorrelated with shifts in preferences should not affect consumption growth once aggregate network resources are controlled for. 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 find that households are unable to smooth consumption when faced with severe health shocks. We pay close attention to a number of econometric problems. First, if illness in period t is predictable, households might already have catered for it in period t-1 (e.g. through savings). Our results would then overestimate the ability of households to smooth truly unpredictable shocks. The second problem is that the interpretation of our results strongly depends on the separability assumption. If utility is not separable between consumption and health, then even perfectly insured households will change their consumption pattern. A third problem is that consumption shocks may be the cause of health shocks and not the other way round. Finally, network formation is endogenous and this could potentially bias our results.

2. MODEL AND ECONOMETRIC SPECIFICATION

Pareto-efficiency in an isolated network

Imagine an isolated network of N households who efficiently allocate risk. They are isolated in the sense that they cannot enter into an insurance arrangement with anyone outside their network. Pareto-efficient allocations can be modelled *as if* all N households pool income in every period and then decide who gets what share of the cake.

Let, for example through some initial bargaining process or via a social planner, each household i get a Pareto-share ω_i of total network income, with ω_i>0, $\forall$ i and $\sum \omega_i = 1$. This Pareto-share will reflect the relative weight of the household in the allocation within the network. 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. If we assume twice continuously differentiable utility functions with U'>0 and U''<0, then, following Mace (1991), Cochrane (1991), Altonji, Hayashi and Kotlikoff (1992) and Townsend (1994), we can write the first order condition of this problem as

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

or its differenced logarithmic equivalent

$$\Delta \ln(U'(C_{it})) = \Delta \ln(\lambda_t) \qquad (2)$$

Equation (2) says that if optimal insurance is attained, then the growth of marginal utility of consumption in a given period should be equal for all households. For any two households *i* and *j* in the network, we can substitute away λ_t in (1) and write the first order condition as

$$\frac{U'(C_{it})}{U'(C_{jt})} = \frac{\omega_j}{\omega_i} \qquad (3)$$

which shows that the marginal utility of each household's consumption reflects its Pareto weight in the program. Following Deaton (1997) and Gertler and Gruber (2002), assume that within-period preferences are of the constant relative risk aversion type and can be represented by

$$U(C_{it}) = (1-\rho)^{-1}\theta_{it} n_{it} \left(\frac{C_{it}}{n_{it}}\right)^{1-\rho} \qquad (4)$$

θ_{it} accounts for intertemporal needs of the household, which are not already captured by the household size, n_{it}. Plugging (4) into (3), taking logarithms and rearranging terms gives:

$$\ln\left(\frac{C_{it}}{n_{it}}\right) = \ln\left(\frac{C_{jt}}{n_{jt}}\right) - \rho^{-1}\left(\ln\theta_{jt} - \ln\theta_{it}\right) - \rho^{-1}\left(\ln\omega_j - \ln\omega_i\right) \tag{5}$$

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)

$$\ln\left(\frac{C_{it}}{n_{it}}\right) = \overline{C}_{NWt} - \rho^{-1}\left(\frac{1}{N-1}\sum_{j=1}^{N-1}\ln\theta_{jt} - \ln\theta_{it}\right) - \rho^{-1}\left(\frac{1}{N-1}\sum_{j=1}^{N-1}\ln\omega_j - \ln\omega_i\right) \tag{6}$$

where $\overline{C}_{NWt} = \frac{1}{N-1}\sum_{j=1}^{N-1}\ln\frac{C_{jt}}{n_{jt}}$ or average (logarithm of) network consumption at time t. Note that the final term in Equation (6) is a time-invariant fixed effect that can be purged out by taking first differences

$$\Delta\ln\left(\frac{C_{it}}{n_{it}}\right) = \Delta\overline{C}_{NWt} - \rho^{-1}\Delta\left(\frac{1}{N-1}\sum_{j=1}^{N-1}\ln\theta_{jt} - \ln\theta_{it}\right) \tag{7}$$

which implies that under the full insurance risk-sharing hypothesis 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 Equation (7) to test the full insurance hypothesis at village level.

Pareto-efficiency in overlapping networks

Now assume there is 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 i, which is member of both networks. From Equation (7) we know that

$$\Delta \ln\left(\frac{C_{it}}{n_{it}}\right) = \Delta\overline{C}_{NW_1 t} - \rho^{-1}\left(\frac{1}{N_1 - 1}\sum_{j=1}^{N_1 - 1}\Delta \ln\theta_{jt} - \Delta\ln\theta_{it}\right) \text{ and} \tag{8}$$

$$\Delta \ln\left(\frac{C_{it}}{n_{it}}\right) = \Delta\overline{C}_{NW_2 t} - \rho^{-1}\left(\frac{1}{N_2 - 1}\sum_{j=1}^{N_2 - 1}\Delta \ln\theta_{jt} - \Delta\ln\theta_{it}\right) \tag{9}$$

which means that

$$\Delta\overline{C}_{NW_1 t} = \Delta\overline{C}_{NW_2 t} + \rho^{-1}\left(\frac{1}{N-1_1}\sum_{j=1}^{N_1 - 1}\Delta \ln\theta_{jt} - \frac{1}{N_2 - 1}\sum_{j=1}^{N_2 - 1}\Delta\ln\theta_{jt}\right). \tag{10}$$

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.

Regression specification

Next, we specify an empirical test to determine 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.

There are two types of costs involved when a household is hit by a health shock. First, there are the medical expenses of consultation and treatment. Secondly there is the income loss due to reduced labour supply of the sick person himself (if he was an income earner) and of any household members who accompany and/or nurse him at the hospital (e.g. wash him, cook for him, etc.).

Say we have some measure of health, denoted by H_{it}, then ΔH_{it} can be interpreted as a health shock. To test for full insurance at village level, Equation (7) can be transformed into the following regression specification:

$$\Delta \ln\left(\frac{C_{it}}{n_{it}}\right) = \alpha\Delta H_{it} + \gamma D_t + \delta\Delta V_{it} + \phi F_i + \varepsilon_{it}, \qquad (11)$$

where V_{it} controls for demographic changes in the household as these could represent shifts in preferences over time. F_i are time-invariant variables like the age, sex and education of the household head, which can proxy for taste shifters that might be correlated with illness. A full set of time dummies, D_t, controls for village level

[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.

variations, including variations of aggregate village resources (Ravallion and Chaudhuri, 1997).[3] Fixed effects controls for unobserved heterogeneity. Gertler and Gruber (2002) estimate (11) without controlling for network effects and find that Indonesian households are unable to smooth 30% of the income loss from severe illnesses.

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 reformulate Equation (11) so that it becomes a test for full insurance at network level:

$$\Delta \ln\left(\frac{C_{it}}{n_{it}}\right) = \alpha \Delta H_{it} + \beta \Delta \left[\frac{\sum_{j \in N_i} \frac{C_{jt}}{n_{jt}}}{\# \mathrm{N_i}}\right] + \gamma D_t + \delta \Delta V_{it} + \phi F_i + \varepsilon_{it} \,. \qquad (12)$$

The null hypothesis under full insurance is α=0, i.e. own health shocks do not affect own consumption once aggregate network resources are controlled for. Furthermore, Pareto-efficient risk-sharing at village level (possibly through overlapping Pareto-efficient networks) implies that β cannot be estimated because aggregate network consumption would then be perfectly collinear with aggregate village consumption. In a situation with partial risk-sharing the significance of β points to the relevance of networks. If networks matter, we would expect β>0.

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

The test for risk-sharing formulated above is defined in 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^{f}_{it} and non-food, C^{nf}_{it}. 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, (1) and (2) are unchanged. Defining U_f as the marginal utility from increasing food consumption, (3) can be rewritten as:

$$\frac{U_f(C_{it}^{f}, C_{it}^{nf})}{U_f(C_{jt}^{f}, C_{jt}^{nf})} = \frac{\omega_j}{\omega_i} \tag{13}$$

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) or (10) can also obtained from (13). 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 (13) that under perfect risk-sharing, individual resources should still not matter, but only network or community resources (Cochrane 1991, p.965). This implies that (11), 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.

econometric problems

Some econometric problems have to be taken into account when estimating Equation (11). The first is that 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. Following Dercon and Krishnan (2000) we tackle this problem by subtracting the predictable part of H_{it} from the measured H_{it}. 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.

The second 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 pattern. The variables in F_{it} have been included to control for shifts in tastes that may be correlated with illness. If they do not properly control for these shifts of taste, however, ΔH_{it} will be correlated with the error term, and its coefficient biased. A third 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 issue again and provide evidence that indicates that the results are not driven by non-separability, nor by health feed-backs.

The fourth 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.[4] Therefore, we instrument changes in average network consumption, using changes in demographic characteristics of network members and remittance flows to network members from outside the network as identifying instruments. 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, demographic movements etc. A few days later individual interviews were

[4] 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

administered to all 220 adult individuals of the village. Questions concerning gifts, loans, labour allocation, income, etc. were then put to the respondents. Gender-sensitive issues were always implemented by enumerators of the same sex as 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, sickness 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. We will confirm this result in the formal tests. Thirdly, risk-sharing via transfers is the most important coping strategy to deal with the consequences of health shocks. This indicates that a correct specification of the 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

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have correlated risk, while households living far away are difficult to monitor, but have uncorrelated risk.

the household.[5] 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.[6] Households clearly cut back on consumption to invest in a house, a bicycle or education. 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), Table 1 suggests that households are far removed from a full insurance situation.[7] 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, with well over half saying that that they were forced to cut back consumption severely. Remember that even some of the shocks categorised under 'deaths' are partly related to an episode of sickness that led to the death. The

[5] The framing of the question in Swahili was as follows: "katika miaka kumi iliyopita, kuna madhara gani ambayo yameathiri kaya yako kiuchumi".
[6] Strictly speaking these are not shocks, but choice variables.
[7] 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).

econometric analysis will confirm that the ability of households to smooth consumption in the face of severe health shocks is very limited.

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, 0-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 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.[8] 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.

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[8] 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.

A response to a substantial number of shocks is taking on extra income earning activities.[9] Casual labour is the most popular and involves doing farm work for others for around TSh 200 ($0.25) for 4 hours of hard work. Qualitative evidence suggests that casual labour is a poor man's coping strategy. Its use may be limited by seasonalities 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. As expected, savings are most important for foreseeable events like lumpy expenditures and ceremonies.

4. DATA AND REGRESSION RESULTS

The self-reported data suggest that households are vulnerable to health shocks. 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. We use the Nyakatoke Household Survey, described in the previous section, to study consumption changes following severe health shocks.

Non-food consumption is measured in between rounds, while the recall period for food consumption is one 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.

This is fine if households switch staple 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 substitute their protein-rich food, like meat and fish, for

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[9] 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.

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 – we will return to this point later.

Table 4 gives the mean and standard deviation of food, non-food (excluding medical expenditures) and total consumption across the five survey rounds. 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 reported in Appendix 1. Note that Nyakatoke is an extremely poor village. Average consumption per household is only about \$8.00 per week, which works out to be just over \$2.00 per adult equivalent unit. The average food-share in consumption is 82%. 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. Price changes across rounds will be controlled for in the regression results by including time 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.[10] This amount is small enough to give us confidence that we are capturing health shocks that matter and not the minor ones. The survey question on which the health dummy is based was meant to capture shocks through reduced labour supply. Three quarters of these cases are adult members of the household, 25% are children below 18 years old and 5% are members older than 70 years old.[11] Even then, we cannot exclude that part of the shock does 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 4373, about 14 times the weekly non-food consumption per adult equivalent.

Before turning to the regression results, we present a simple, univariate analysis of the relation between consumption and illness. The second row shows that households with health shocks have an average consumption downfall of 5.2%. Looking at their relative movement within the village, makes their situation seem even worse. Those who do not experience any shocks (i.e. their index remains constant, or they go from sick to healthy) experience a rise in income of 5.1%.[12] The two last columns show that this drop in consumption is completely caused by a drop in non-food consumption, while growth in food consumption is not different. We will come back to this issue when discussing the regression results.

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[10] 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).

[11] 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.

[12] Recall that consumption has not been deflated. In the regression analysis below we will correct for price changes through time dummies.

In the empirical test, we need to control for network consumption, without making any a priori assumption about who the network partners of each household are. 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. Figure 1 shows all the links between households in the village and shows that these networks are strongly overlapping. This way we can calculate the average consumption of the network of each household (excluding the household itself) and include it as a regressor to control for network consumption (the second RHS term in Equation (12)). 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, the network partners of ones network partners are also included.

Network formation is endogenous and this could bias β. Fixed effects purges the regression of any time-invariant factors which determine network formation. Still, we can expect some spurious correlation between the change in network consumption and the change in own consumption if network partners are chosen according to, for example, profession and geographical distance.[13] We identify changes in network consumption by the change in mean demographic characteristics of the network partners and by the change in the mean value of remittances received from outside the network. These are two variables that we expect to be strongly correlated with network consumption, but not with own consumption.

Preference shifts are controlled for by including changes in household demographics (6 age-sex categories). As further controls we include the age, sex and education of the head. Means and standard deviations of these variables are reported in Appendix 2. Time dummies capture any village effects (including fluctuations of aggregate village resources and prices). Remember that the fixed effects purges out any unobserved heterogeneity.

Results are given in Table 6. We give IV-estimation results, treating network consumption as endogenous, and we report results based on measured health shocks, and those purged of the expected part of the health shock. Results for total consumption, as well as for food and non-food consumption are reported. We report results using two definitions of aggregate network resources, the first defining networks by the direct network partners, the second by direct and indirect partners. We enter them both separately and together.

All the results using total consumption seem to suggest that health shocks cause consumption to drop with roughly 6%, but the results are not strongly significant – using measured shocks this result is only significant at about 12 percent. In the next columns we split consumption into its food and non-food components. Food consumption seems not to be affected by health shocks. Non-food consumption is

[13] De Weerdt (2002) and De Weerdt and Van de gaer (2002) analyze the factors that underlie network formation in the village.

quite strongly affected – by about 21-30%, and these effects are significant at 5% or less.[14] In all regressions, the coefficients on unexpected and total health shocks are almost exactly the same, suggesting that this correction is relatively unimportant. Overall, this suggests that full risk-sharing is rejected – for total consumption only at 12 percent using the overall health shock, but with much stronger evidence when focusing on non-food consumption.

What might explain this difference in findings between food and non-food consumption? Given that full risk-sharing is rejected, this does not need to be very surprising. First, the income elasticity for food is bound to be lower than for non-food – so that if an income shock, caused by a health shock hits the household, non-food consumption is likely to be most responsive. The point estimates of the coefficients are consistent with this interpretation. Local conditions make the larger responsiveness of non-food consumption also very plausible. First, in Haya villages self-insurance for food consumption is relatively easy (at least compared to certain other rural societies). Food is easily stored (a banana field can go on bearing fruit for some time without much tending to and there is always plenty of cassava in the ground at any time of the year). Other crops, which have a clear harvesting period (beans, maize, etc...), are stored as food in the house. However, the main staples, such as bananas or cassava are not easily or commonly traded, being bulky relative to value, so stocks will often not be monetised when shocks occur. Food consumption will then be relatively easily kept smooth, but non-food consumption would take the larger part of the adjustment. Furthermore, even if partial risk-sharing occurs[15], it is probably relatively easier to get food assistance from neighbours and friends, than

[14] Gertler and Gruber (2002) also run separate regressions for food and non-food consumption. In their data they find that both types of consumption are equally affected by health shocks.

getting cash assistance from them. Donors may wish to tie their transfer to exclude false claims by the recipient or because they have paternalistically altruistic preferences (Pollack, 1988). Alternatively, donors may prefer to make food transfers, because they have less bite in the budget constraint than cash related non-food transfers.

The results of Table 6 show that consumption feed-backs into health are not driving our results. If consumption shocks were causing illness shocks, we would expect to see this effect working through food consumption, which is not the case. The fact that food consumption does not vary with health shocks also goes some way to refuting the non-separability hypothesis, as it is commonly assumed that non-separability of consumption and health works through reduced consumption of food by the sick person. Even if health shocks were to shift preferences for non-food items, it is unlikely that the preferences of one individual in the household could have such a huge effect on the non-food consumption of the whole household, given that the average household size is 4.7.[16]

As a further test of the possibility that non-separability is driving our results, we use an alternative endogenous variable. At the end of the survey we asked the respondents to reflect on the different periods of the year which corresponded to the survey rounds. We asked them when their economic situation was good and when it was bad rated from 1 (very good) to 5 (very bad). The responses provide us with an aggregate economic index, indicating how the respondent sees his general economic position in that round. The key point is that this index captures how hard the budget

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[15] Recall that the rejection of perfect risk-sharing may imply either partial or no risk-sharing.
[16] A similar argument is given by Gertler and Gruber (2002).

constraint bites and should be free from any preference shifts.[17] Thus it can serve as an alternative measure of consumption, with the added advantage that non-separability cannot distort the results. We re-estimated Equation (12), but replaced consumption by the self-reported economic index. The results of this exercise (not reported) show that shocks have a statistically significant effect (at 1%) in terms of reducing the overall economic position, raising the index with roughly 30%.

Finally, what can we conclude about the functioning of networks? First note that we treat these as endogenous and use remittances to the networks, network-level demographic and livestock values as instruments. The Hansen J-statistic is used to test the validity of these instruments.[18] In all cases, the null hypothesis cannot be rejected at 5% or less, so no problems with the instruments are detected. We entered changes in the logarithm of network consumption of the direct network partners, as well as the relevant changes for direct and indirect network partners. When entering them together, we investigate whether controlling for proximate networks, a broader definition of networks adds anything.

While our results confirm that the village does not provide full insurance to households, they also suggest that even small tightly-knit networks do not fully insure consumption. This result can be derived even without looking at the coefficient of network consumption: full risk-sharing has been rejected, and this is particularly reflected in fluctuations in non-food consumption.

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[17] One could argue that when a household member is ill the household is bound to say that the situation is bad. When collecting the data for this question, we took time to explain first that we were talking of only the *economic* situation of the household. The core Swahili word we used to make this distinction was "*hali ya uchumi*" (lit. the state of the 'economy' of your household). Furthermore, only about two thirds of the households who have a health shock have a decline in their aggregate shock index.

The hypothesis that food consumption can be kept smooth in the face of idiosyncratic shocks cannot be rejected, but 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.[19] 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. Whether food transfers are behind this result cannot be established from these data. Food consumption smoothing via storage may also account for this result, with the insignificance of the network coefficients simply following from the irrelevance of networks for consumption smoothing. The qualitative evidence discussed in section 3 (table 3) provides some evidence that both may play a role.

The coefficients of network consumption in the case of non-food consumption provide clearer evidence regarding the role of networks. Recall that idiosyncratic shocks appear to result in consumption fluctuations, implying the rejection of full risk sharing. We find evidence that networks play a role in sustaining non-food consumption via partial risk-sharing. In this case, and given controls for village level resources, a positive and significant coefficient on network consumption provides

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[18] 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 J-statistic is consistent if errors are heteroskedastic.

evidence for this, since there is little reason for this to happen if all mutual support occurs at the village level or if consumption smoothing occurs via the depletion of stocks and assets. This evidence is clearest in column (16) to (18). Using unexpected shocks only, changes in the consumption of direct partners is significant at 5%. In column (18), the network variables are positive and jointly significant at 7%; but since changes in consumption using the larger network definition are not significant in (17), this suggests that the more narrow definition of the network is more appropriate. This suggests that some form of partial risk-sharing appears to occur in these villages, and that only direct network partners form the relevant group. This may indicate substantial costs to flow across nodes in the network. It also means that treating overlapping networks as a single network may be misleading.

As a final test of the robustness of our results, we tried to further address measurement error in network consumption, using the aggregate economic index mentioned before. Since this aggregate economic index can be viewed as an independent way of measuring current conditions, with measurement error that is likely to be uncorrelated with measurement error in consumption, we used the average network index as an additional instrument in our regression. The results, both in terms of coefficients and standard errors, were virtually unaffected, suggesting that measurement error is not affecting the thrust of our results.

5. CONCLUSION

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[19] De Weerdt (2002) shows that all households in the village are connected to each other if one allows for five steps across the network (i.e. the maximal geodesic distance in the network equals five).

When respondents in Nyakatoke were asked to mention the two worst shocks over the past 10 years, health shocks were most frequently mentioned. In well over half of these cases, the illness was reported to have severely cut back the daily consumption of the household and only 8% reported to have suffered no loss in consumption. Formal statistical analysis confirms these self-reported data. Using panel data we have found that households fail to cope with severe health shocks. They have to cut back non-food consumption drastically to cope with the loss of income and to pay their medical bills. This result is all the more striking, because we have tested full insurance in small networks of self-selected households. Cash-related full insurance is not achieved, not even in very small networks. At the same time, we find that networks matter for consumption smoothing, and the village is not the appropriate unit for partial or full risk-sharing analysis.

One reason for this failure may be that, even at this level, problems of information and enforcement distort optimal outcomes. Another reason may be that Pareto-efficiency is not achieved *because* all networks are intertwined with each other. If households have obligations in several networks at the same time, then full insurance would imply insuring your network partner for any claims made upon him by his other partners (with whom you might not have a direct link). It is quite conceivable that households have built in contingencies to limit such reinsurance claims and that this prevents full insurance to be attained, even within the confines of small networks. Surprisingly, very little work has been done on frictions in flows of resources between different insurance networks. A priori, one would expect frictions to be relatively high in insurance networks (e.g. compared to information networks).

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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 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 & 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	%[1]	N	%[1]
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[2]	*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

Notes: 1. The denominator is the total number of shocks that were mentioned (296).
2. 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.

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 & court cases	33	28	40	15	0
shock in income gen. act.	12	32	32	44	0
others	32	24	36	32	0
TOTAL	43	41	37	18	0

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

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

	total consumption	food consumption	non-food consumption
ROUND 1	1646	1182	460
	(1159)	*(577)*	*(828)*
ROUND 2	1446	1206	239
	(734)	*(563)*	*(258)*
ROUND 3	1557	1309	259
	(805)	*(671)*	*(263)*
ROUND 4	1791	1440	351
	(1141)	*(719)*	*(792)*
ROUND 5	1722	1457	265
	(759)	*(660)*	*(264)*
TOTAL	1632	1317	316
	(945)	*(648)*	*(558)*
N	566	570	566

Source: Nyakatoke Household Survey

NOTE: in each cell the top number is the mean and the bottom one (between brackets) the standard deviation.

Table 5: Impact of health shocks on consumption: average consumption change between rounds (in percent).

health shock	% of pooled sample	Δln total consumption	Δln food consumption	Δln non-food consumption
no	89	0.051	0.068	-0.010
yes	11	-0.052	0.052	-0.426
TOTAL	100	0.040	0.066	-0.054

Source: Nyakatoke Household Survey
Note: *N*=402; because we look at first differences, we 'lose' one round of observations.

Table 6: Testing risk-sharing and network effects. LHS=changes in log consumption per adult (i.e. fixed effects within estimator). IV regressions with robust standard errors. Z-scores in brackets.

	Total Consumption					
	(1)	(2)	(3)	(4)	(5)	(6)
Health shock	-0.06 (1.50)	-0.05 (1.37)	-0.06 (1.47)			
Unexpected part of the health shock				-0.06 (1.30)	-0.05 (1.17)	-0.06 (1.20)
Change in consumption of direct network partners	-0.27 (0.84)		-0.10 (0.35)	-0.01 (0.04)		0.12 (0.46)
Change in consumption of direct and indirect network partners		0.58 (0.63)	1.25 (1.39)		0.55 (0.57)	0.60 (0.67)
p-value for joint significance F	0.00	0.00	0.00	0.00	0.00	0.00
p-value for Hansen J-Statistic	0.06	0.58	0.29	0.17	0.69	0.49
	Food Consumption					
	(7)	(8)	(9)	(10)	(11)	(12)
Health shock	-0.01 (0.45)	-0.01 (0.23)	-0.01 (0.44)			
Unexpected part of the health shock				-0.01 (0.16)	0.00 (0.09)	-0.01 (0.17)
Change in consumption of direct network partners	-0.01 (1.15)		-0.23 (1.04)	-0.31 (1.09)		-0.29 (1.13)
Change in consumption of direct and indirect network partners		0.25 (0.22)	1.27 (1.17)		0.14 (0.11)	0.62 (0.58)
p-value for joint significance F	0.00	0.00	0.01	0.00	0.00	0.00
p-value for Hansen J-Statistic	0.19	0.91	0.69	0.38	0.92	0.78
	Non-Food Consumption					
	(13)	(14)	(15)	(16)	(17)	(18)
Health shock	-0.24 (2.76)	-0.24 (2.85)	-0.21 (2.29)			
Unexpected part of the health shock				-0.24 (2.39)	-0.29 (2.92)	-0.22 (2.16)
Change in consumption of direct network partners	-0.06 (0.12)		-0.17 (0.46)	0.87 (1.99)		0.54 (1.54)
Change in consumption of direct and indirect network partners		0.82 (0.64)	2.23 (1.70)		0.83 (0.67)	1.49 (1.41)
p-value for joint significance F	0.00	0.00	0.00	0.03	0.05	0.04
p-value for Hansen J-Statistic	0.15	0.59	0.45	0.64	0.52	0.40

Source: Nyakatoke Household Survey

Note: absolute values of the *z*-scores are given in brackets under the coefficient. All regressions include the change in 6 demographic categories (males and females aged 0 to 5, 6 to 15 and 16+) and controls for the age, sex and education of the household head. The latter is a dummy variable indicating whether or not the head has completed primary. 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. In the IV regressions, changes in the log of average network consumption are identified by changes in the mean value of remittances network partners receive from their none-network partners, changes in the mean values of livestock owned by households in the network and by the changes in their mean demographic characteristics. The regressions for health shocks are based on 402 observations. The regressions for *unexpected* health shocks are based on 294 observations (we lose one round because lagged consumption is explains predicted health). Tests statistics reported include the p-value for the Hansen J-statistic.

APPENDIX 1: The network graph of Nyakatoke. Each dot is a household, each line a link. The map has been drawn using a program called DOTTY from Graphiz.

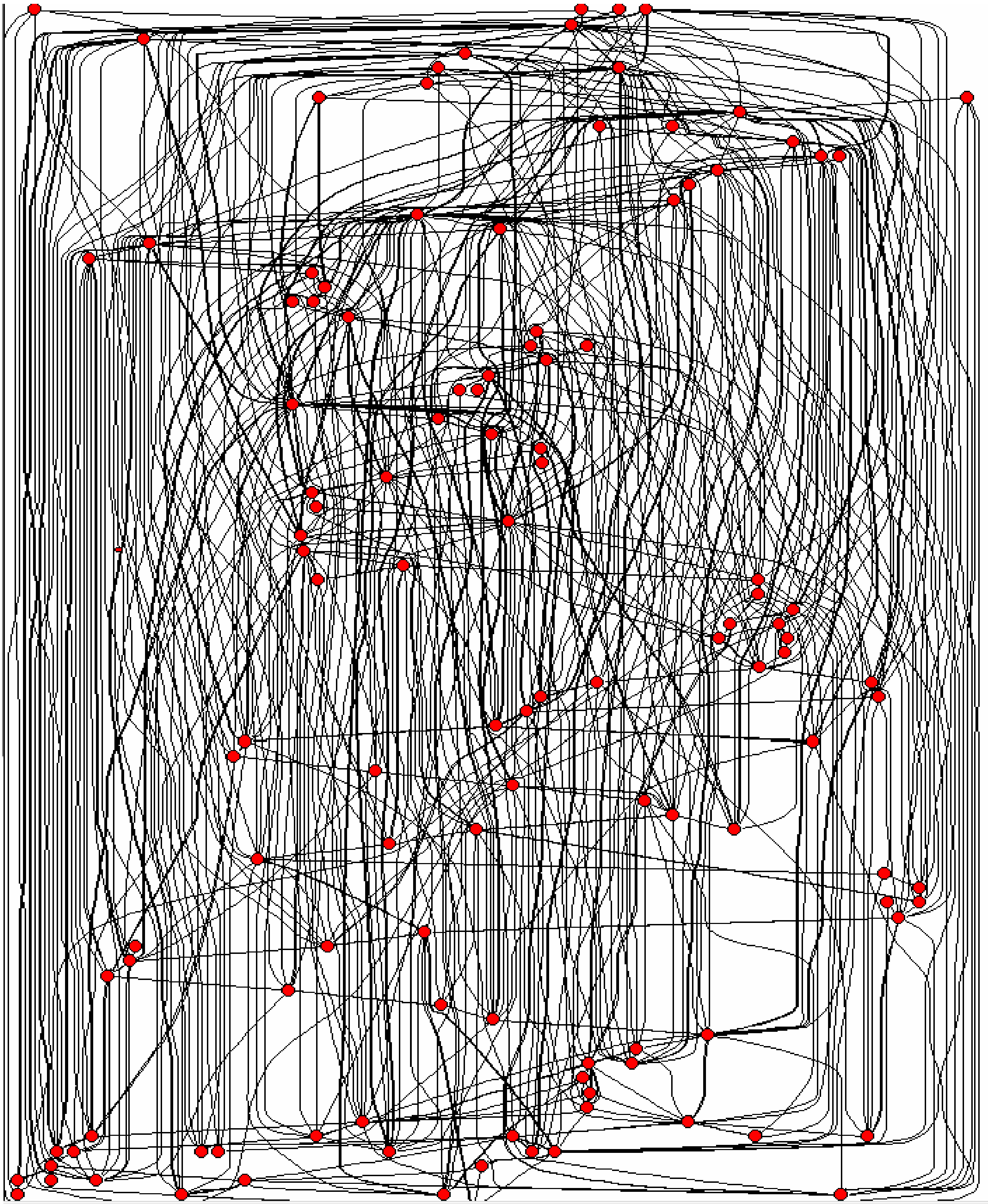

Table Appendix 1: adult equivalence scales.

AGE	MALE WEIGHT	FEMALE WEIGHT
0	.33	.33
1	.46	.46
2	.54	.54
3-4	.62	.62
5-6	.74	.70
7-9	.84	.72
10-11	.88	.78
12-13	.96	.84
14-15	1.06	.86
16-17	1.14	.86
18-29	1.04	.80
30-59	1.00	.82
60+	.84	.74

Note: Based on World Health organisation equivalence scales quoted in Dercon (1998) and McCulloch (1999).

Table Appendix 2: descriptive statistics of regressors (across the pooled sample).

VARIABLE	*N*	MEAN	S.D.
male members between younger than 5	585	0.5	0.7
male members between 5 and 15	585	0.6	0.8
male adults	585	1.1	0.9
female members younger than 5	585	0.5	0.7
female members between 5 and 15	585	0.7	0.9
female adults	585	1.3	0.7
age of the household head	119	45	16
head has completed primary education (no=0, yes=1)	119	0.60	0.5
sex of the household head (female=0, male=1)	119	0.79	0.4

Source: Nyakatoke Household Survey