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RISK MANAGEMENT AND SOCIAL VISIBILITY IN GHANA

Abstract: In this paper we test for risk pooling within and among social networks to see if the extent of informal insurance available to individuals in rural Ghana varies with their social visibility. We identify a distinct subpopulation of socially invisible individuals who tend to be younger, poorer, engaged in farming, recent arrivals into the village who have been fostered and are not members of a major clan. While we cannot reject the null hypothesis that individual shocks do not affect individual consumption and that individual consumption tracks network and village consumption one-for-one among the socially visible, risk pooling fails for the socially invisible subpopulation. These results have important implications for the design of social protection policy.

1. Introduction

Risk management is crucial to economic advance, indeed to the very survival, of people in low-income, agrarian countries. In the ideal Arrow-Debreu world, complete markets with symmetric information would provide an array of state contingent contracts and all decision-makers in the economy could make welfare improving exchanges based on each other's known preferences and beliefs over states of the world. In this fictional framework all risks can be addressed with market-based solutions.

In reality, information asymmetries and covariate risk impede risk management in general, especially through formal financial institutions. Rural populations therefore depend heavily on informal institutions for managing risk in the absence of well-developed insurance markets.[1] But access to informal insurance is not necessarily uniform. Certain subpopulations may have superior access to the desirable intertemporal consumption smoothing made possible by informal insurance mechanisms (Dercon and Krishnan 2000, Dercon 2005, De Weerdt 2005, Santos and Barrett 2006).

So how effectively do social networks provide substitute insurance where formal financial markets fail? Who is left out of informal risk management institutions? Since informal institutions are based on endogenously formed social networks among and within households, for whom is reasonably complete (i.e., Pareto efficient) risk pooling available? And since distinct networks commonly intersect through shared members, do these interlinkages create effective informal re-insurance, wherein shocks within one social network get reinsured (at least partly) by other networks within the village?

To address these issues we draw on several threads in the literature. The first thread is the literature on risk pooling and social insurance. Empirical tests often reject the null hypothesis of full (Arrow-Debreu) social insurance within rural communities (Deaton 1992, Townsend 1994, Gertler and Gruber 1997). Even allowing for potential difficulties in insuring covariate risk – i.e., shocks experienced, at least in part, by all members of a social unit – the existing literature suggests that informal insurance of idiosyncratic (i.e., individual- or household-specific) risk is far from complete. Issues pertaining to measurement error, asymmetric information and contract enforcement have

[1] See Alderman and Paxson (1992), Besley (1995) and Bardhan and Udry (1999) for complete reviews.

been identified as possible reasons for incomplete risk pooling (Alderman and Paxson 1992, Murgai et al. 2001). One could argue that the hypothesis of full insurance will necessarily be rejected because these tests are typically conducted for exogenously given groups such as the entire village, community, or ethnic group and such exogenously defined groups might not accurately reflect the true domain and scope of risk sharing.[2] In addition, most studies of the extent of social insurance have been undertaken at the household level, implicitly assuming a unitary household model and thus perfect substitutability among decision-makers as well as pooling of all resources within the household. Yet there is ample evidence in the literature rejecting each of these assumptions, including within the context of social insurance (Dercon and Krishnan 2000).[3]

This leads to the second thread of the literature on which we build. Social networks have long been identified as key loci of informal risk sharing. Individuals establish networks based on a wide range of individual and mutual attributes, including but not limited to kinship ties, ethnicity, geographical proximity, occupation, wealth, religion, and gender (Goldstein 1999, Santos and Barrett 2004, Udry and Conley 2005, De Weerdt 2005, DeWeerdt and Dercon, 2006, Fafchamps and Gubert 2007). However, some marginal groups may be less well connected in social networks and may thereby enjoy less informal insurance access than do wealthier or more powerful members of a community (Dercon 2002, De Weerdt 2005, DeWeerdt and Dercon 2006, Santos and Barrett 2006). If social network formation is commonly asymmetric, in the sense that an agent's latent demand for a link with another is a function not just of the absolute social distance between the two, but also of their ordinal position – e.g., male-female versus female-male, or poorer or wealthier (Santos and Barrett 2004, DeWeerdt and Dercon, 2006, Fafchamps and Gubert 2007) – then what appears in the literature as wealth differentiation in insurance access could be due to differential social visibility based on individual characteristics, i.e., due to visibility that is correlated with but distinct from wealth.

[2] See Goldstein et al. (2005), Santos and Barrett (2006).
[3] See Alderman, Chiappori, Haddad, Hoddinott and Kanbur (1995), Doss (1996), Udry (1996), Goldstein (1999) and Duflo and Udry (2004) for evidence on intrahousehold allocation issues.

We hypothesize, in particular, that social connectedness is the key issue in access to informal social insurance and that social visibility is not random but, rather, reasonably predictable based on individuals' observable characteristics. Those who are relatively socially invisible, meaning they are not widely known in the community, may get left out by default, while those who are well known in the community enjoy the sort of social insurance widely hypothesized in the literature. Moreover, in so far as there exist distinct social networks that are interconnected through shared members, then social insurance among (not just within) networks may provide a sort of social re-insurance of individual-specific, idiosyncratic risk. If geographically-defined populations of the sort used in standard empirical analysis mix the socially visible and the socially invisible, widespread evidence of partial risk pooling could well mask reasonably complete risk pooling for those with extensive social networks and negligible risk pooling for the socially invisible. The practical implication of such a finding would be straightforward: target external safety net interventions towards covariate risk and to those likely to be socially invisible, and try not to waste resources on external safety nets for the idiosyncratic risk faced by those socially visible persons for whom informal insurance seems to offer reasonably complete risk pooling.

In this paper we therefore test for risk pooling within and among social networks, as well as within villages, to see if the extent of informal insurance available to individuals in rural Ghana varies by their social visibility. The key results are as follows. (i) There exists a small but distinct subpopulation of socially invisible individuals within the sample villages. The socially invisible tend to be younger, engaged in farming, recent arrivals into the village who have been fostered and are not members of a major clan. (ii) Risk pooling is substantial for the socially visible; we cannot reject the null hypothesis that individual shocks do not affect individual consumption and that individual consumption tracks network and village consumption one-for-one. (iii) On the other hand, risk pooling fails for the socially invisible subpopulation. We overwhelmingly reject both the null hypothesis that individual shocks do not affect individual consumption and the null that individual and network or village consumption move together one-for-one for those individuals who appear socially invisible.

The remainder of the paper proceeds as follows. The next section lays out the familiar general equilibrium model of risk pooling and uses limiting conditions on the extent of an agent's social network to derive exclusionary restrictions for econometric hypothesis testing. Section 3 then describes the data. Section 4 explores the concept of social invisibility and identifies the characteristics of those persons we label socially invisible in this sample. Section 5 tests for risk pooling within and among social networks. Conclusions and policy recommendations are presented in Section 6.

2. Risk Pooling and Social Visibility: Simple Theoretical Predictions

Shocks are pervasive in most agrarian societies, the study area in Ghana being no exception. To what extent are shocks insured so that individuals can smooth consumption and thereby improve intertemporal welfare? Is risk fully pooled at the village level or at the network level? Does the extent of risk pooling depend on an individual's social visibility? To address these questions, we use a standard model akin to that of Townsend (1994).

Suppose there are S possible states of the world, each occurring with objective, constant and commonly known probability π_s. No formal financial (credit, insurance or savings) products are available in this economy. Assume individuals have preferences that are additive across time and over states of nature and common rates of time preference, τ, where λ_{in} is the programming weight associated with individual i in network n. Suppose there are K social networks in the economy with N members in each network.[4] Let c_{inst} and y_{inst} be individual i in network n's consumption and income in state s at time t, respectively. Then we can denote the Pareto efficient allocation of risk by the following problem:

$$\max_{c_{inst}} \sum_{i=1}^{N} \lambda_{in} \left[\sum_{t=0}^{T} \sum_{s=1}^{S} \tau^t \pi_s U\left(c_{inst}\right) \right] \tag{1}$$

[4] Clearly network sizes vary across individuals. Adding that complexity to this model affords no extra insights but does complicate the notation, so we make the innocuous simplifying assumption that all networks are of equal size. For now we also abstract from the fact that networks may be interlinked: an individual may belong to more than one network. We explore this possibility below in examining empirically the extent to which risk is spread among social networks.

subject to

(2) $$\sum_{i=1}^{N} c_{inst} = \sum_{i=1}^{N} y_{inst} \quad .$$

The first order condition allocating consumption among two individual network members, i and j, is given by

(3) $$\lambda_{in} U'(c_{inst}) = \lambda_{jn} U'(c_{jnst})$$

Suppose each individual's preferences can be represented by an exponential utility function

(4) $$U(c_{inst}) = \left[-\frac{1}{\alpha}\right] \exp[-\alpha c_{inst}] \quad .$$

Then substituting (4) into (3), taking logs and rearranging terms, we get

(5) $$c_{inst} = c_{jnst} - \log\left[\frac{\lambda_{jn}}{\lambda_{in}}\right] \quad .$$

Then aggregating across all individuals in a network gives

(6) $$c_{inst} = \frac{1}{N}\sum_{j=1}^{N} c_{jnst} + E_{in}$$

where

(7) $$E_{in} = \frac{1}{\alpha}\left[\log\lambda_{in} + \frac{1}{N-1}\sum_{j=1}^{N-1}\log\lambda_{jn}\right]$$

which implies that

(8) $$c_{inst} = \bar{c}_{nst} + \mathrm{E}_{in}$$

where $\bar{c}_{nst}$ is the network mean consumption excluding *i* and E_{in} is a constant that allows for dispersion in consumption levels among network members that is fixed over time and states of nature. The strong implication of Pareto efficient risk pooling, as reflected in equation (8), is that contemporaneous own income, y_{inst} is irrelevant to the determination of individual consumption. We can decompose the income in state *s* at time *t* of agent i, who belongs to network *n*, into a permanent component $\overline{y}_{in}$ and an idiosyncratic component, $\tilde{y}_{inst}$, where the latter represents a mean zero, i.i.d transitory income shock that causes period-specific income to deviate from her long-run average ($\overline{y}_{in}$). Own income is thus:

(9) $$y_{inst} = \overline{y}_{in} + \tilde{y}_{inst}$$

Introducing (9) into (8) implies a testable exclusionary restriction for full insurance:

(10) $$c_{inst} = \beta\left(\overline{y}_{in} + \tilde{y}_{inst}\right) + \gamma\overline{c}_{nst} + \delta \mathrm{E}_{in}$$

Taking first differences in time yields the estimable equation

(11) $$\Delta c_{inst} = \beta\Delta\tilde{y}_{inst} + \gamma\Delta\overline{c}_{nst} + \varepsilon_{inst}$$

Where Δ is the first difference operator and ε_{inst} is a mean zero, i.i.d error term. A test of the full risk pooling hypothesis is then H_0: β=0, γ=1 versus H_A: β>0 or γ<1. An analogous test of the full risk pooling hypothesis at village level emerges from substituting change in mean consumption in village *v* (excluding agent i) for that in network *n* in equation (11). Similarly, the null hypothesis that distinct social networks within a village pool risk can be derived by substituting $\Delta\overline{c}_{nvst}$ as the dependent variable and $\Delta\overline{c}_{-nvst}$ for the second term in equation (11), respectively, where $\Delta\overline{c}_{nvst}$ is the mean consumption for individual *i*'s network and $\Delta\overline{c}_{-nvst}$ is the residual mean for all other networks in the village excluding individual *i*'s.

The implication of the above framework for those who are socially invisible – i.e., for whom N=1 because they are the entirety of their own social network – is immediately obvious. The summation operators in equations (1) and (2) drop away, the social allocative efficiency conditions in (3) and (5) disappear, and the key exclusionary restrictions in equation (11) are thus turned on their head. For those without recourse to social insurance networks, there should be no risk pooling, thus H_0: β=1, γ=0 versus H_A: β<1 or γ>0. Note that the point is not that certain subpopulations lack the means to insure one another; it is that variation in social connectedness irrespective of financial means matters to one's access to social insurance networks. This basic insight that the extent of the social network fundamentally influences the relation between individual-level income shocks and individual consumption, i.e., the risk pooling capacity of the individual, implies a need to first define and measure social visibility before testing standard risk pooling hypotheses because social visibility conditions the appropriate test specification.

3. The Data

The data used in this paper are from a rural household survey undertaken in the Akwapim South District (specifically, the Nsawam - Aburi area) in the Eastern Region of Ghana from July 2004 to January 2005. This was the third wave of a panel data set initiated by Chris Udry and Markus Goldstein and described in detail in Goldstein and Udry (1999). Since the early 1990s farmers in this area have been switching from the cultivation of maize-cassava intercrop for domestic production to pineapple cultivation for export. This transition involves a significant amount of risk associated with transitioning to new agronomic practices and marketing arrangements, as well as potential disruption of traditional social arrangements.

The original sample was selected using a two-stage procedure. Four village clusters were purposively selected based on their participation in fruit and vegetable production as well as their agronomic, market access and geographic conditions. Sixty married couples (or triples) were then randomly selected in each village cluster, except for the smallest village cluster, where all resident couples were included.[5] Each individual selected was interviewed separately. Male enumerators were assigned to male respondents and female enumerators to female respondents to preserve gender sensitivity and cultural norms.

Three rounds of data were collected at approximately eight week intervals, rotating between pairs of villages.[6] The first round of data was collected in September-

[5] We loosely refer to village clusters as villages for ease of notation.

[6] Given budgetary constraints, each enumerator was assigned to one of two villages in pre-assigned pairs. Based on geographic proximity, the first village pair comprised of villages 1 and 4, whereas the second village pair comprised of villages 2 and 3. Interviews were conducted simultaneously in the two villages in a given pair, after which the enumerators moved to the other pair. We spent approximately four weeks in

October 2004. The second round was conducted October-November 2004. The third round was conducted from late November 2004 through January 2005. Across the four villages, 372 individuals were surveyed in the first round. The second and third rounds had sample sizes of 371 and 350 individuals, respectively. The sample attrition rate was thus 0.3% between the first and second rounds and 5.9% between the first and third rounds.[7]

The subsections that follow offer brief descriptions of the key modules relevant to our analyses. Other standard variables associated with household composition, asset holdings, family background, etc. are likewise employed in the regression analysis in section 5 and described below.

3.1 Individuals' Social Networks

For each respondent, we randomly selected seven individuals in the sample from the same village (without replacement).[8] We then asked each respondent about their knowledge of the match i.e., "Do you know__?", followed by a series of questions about their relationship with each of these matched individuals: how often they talked with them, and whether or not he/she could approach the individual to deal with any of a set of specific issues related to farming and credit. In administering the questionnaire we made a clear distinction between knowing *of* someone (i.e., using the Akan translation of just "having heard of the person") and actually knowing the person in the sense of mutual acquaintance. Knowing a random match in this sense is indicative of an extant social link. This gives us a random sample not only of individuals but also of prospective social relations, which is the preferred method of sampling social networks (Santos and Barrett 2007). By design, the characteristics of these random matches are representative of

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one pair of villages, moved to the next pair for next four weeks, and continued this pattern of rotation for the duration of the study.

[7] A simple attrition probit was estimated using robust standard errors, with the dependent variable *ATTRIT*=1 if individuals were lost between rounds 1 and 3, = 0 otherwise. The estimation results indicate that individuals lost between rounds 1 and 3 were more likely to be younger males whose parents had held village offices. Neither wealth nor the incidence of any of the shocks used in the subsequent analyses was statistically significant in explaining patterns of attrition.

[8] Respondents were also non-randomly matched with three other village-specific "focal" individuals identified from the community-studies approach taken in a preliminary field trip as individuals in the villages from whom advice is commonly sought. We focus on the random matches in this study.

people with whom they have (and do not have) extant social links, i.e., it provides an unbiased representation of the structure of their social networks.

3.2 Consumption

Detailed data were collected on purchased food, general family expenses and personal expenditures by each respondent in the household.[9] Even though these expenditure questionnaires were administered at the individual level, with the head and spouse(s) of head being interviewed separately regarding contributions made towards purchasing an item, individual expenditures were not assigned. Hence, we follow Goldstein (1999) in assigning particular items as purchases for own-consumption: alcoholic beverages, non-alcoholic pre-packaged beverages, prepared food (from kiosks), personal care products, hair cuts, public transport, petrol, car repairs, newspapers, entertainment, lottery tickets and kola nuts.

Table 1 presents the mean and standard deviation of expenditure on these goods purchased for own-consumption per village and round as well as the share of total expenditure incurred by each respondent on purchased food, general family needs and personal items spent on these assigned individual items in a typical month. On average, respondents spent 393,383 Cedis; 306,422 Cedis and 379,544 Cedis in rounds 1, 2 and 3, respectively.[10] These values account for 16%, 19% and 18% of total expenditures in rounds 1, 2 and 3, respectively. Village 4 had the least individual expenditures.[11]

3.3 Shocks

Respondents were asked about a series of prospective idiosyncratic shocks. We selected four types of shocks: (i) value of damage caused by general farm problems; (ii) total curative health care expenses; (iii) value of personal items stolen; and (iv) funeral expenses upon sudden death of family member. For each of type of shock we asked about the out-of-pocket expense incurred as a result of that shock or the imputed value of

[9] Recall periods varied by expenditure based on the modal frequency of purchase reported in waves 1 and 2. These essentially intra-annual expenditure were converted to nominal monthly rates.
[10] The mean exchange rate over the survey period was roughly 9000 Cedis/ US$1.00.
[11] This relatively modest share of total household expenditures arises from the need to match clearly individual expenditures with individual-specific social visibility. In so far as the visibility of a household's adult members reflect its overall visibility, the analysis carries through to household and more aggregate units of analysis. Indeed, we later explore network level re-insurance.

damage experienced. Table 2 presents the frequency of shocks faced by respondents as well as the nominal mean response expenditures and imputed values of damage caused by these shocks by round.

Overall, 92% of respondents reported suffering at least one of these shocks in round 1. 83% and 79% reported experiencing a shock in rounds 2 and 3, respectively. By way of percentage of individuals affected, health shocks were the most frequent in rounds 1 and 3, while sudden death within the family was the most frequent shock experienced in round 2. Over all three rounds, 57% of the respondents reported having suffered health problems and 51% had suffered a sudden death in the family. Morbidity and mortality thus pose a huge financial burden on families in this area. In addition, 32% of the respondents suffered from at least one of a variety of farm problems, the most prevalent being infestation by grasscutters (a common rodent in the area). Only 15% of the respondents experienced theft of a personal item. While the questions were focused on idiosyncratic shocks, covariate risk associated with rainfall and price patterns did not appear to be the primary concern in these communities. This is consistent with a growing body of empirical evidence that suggests idiosyncratic risk dominates covariate risk in rural Africa and Asia (Udry 1991, Townsend 1995, Deaton 1997, Lybbert et al. 2004, Morduch 2004, Kazianga and Udry 2006).

Not only were shocks commonplace, they were also very costly. The total value of losses due to shocks was 2640621 Cedis in round 1, 492290 in round 2 and 415992 in round 3. These figures correspond to 109%, 49% and 32% of total expenditures incurred by respondents on purchased food, family and personal items in rounds 1, 2 and 3, respectively. Even though few people reported experiencing theft of personal items, this shock was associated with huge losses. This was the most serious shock in rounds 2 and 3, in terms of the magnitude of imputed value of loss. Health shocks were the most serious in round 1. By way of share of total expenditure captured by the value of loss, health shocks were the most important at 58% and 51% in rounds 1 and 2, respectively, with theft of personal items accounting for 39% in round 3. The magnitude of these shocks relative to household expenditure levels underscores that idiosyncratic shocks can imperil the accumulated assets of households if they have insufficient (formal or informal) insurance. Hence our desire to understand who is reasonably well insured.

4. Social Invisibility

Although much discussion of informal insurance implicitly assumes that everyone participates equally in the social networks that mediate interhousehold transfers, recent studies find significant intra-village variation in social connectedness, with a non-trivial share of individuals relatively isolated from other residents (Santos and Barrett 2006). Historical accounts from Africa confirm this pattern, emphasizing the correspondence between extreme poverty and limited social interactions. For example, Iliffe (1987, p.42) notes that "[t]o be poor is one thing, but to be destitute is quite another, since it means the person so judged is outside the normal network of social relations and is consequently without the possibility of successful membership in ongoing groups, the members of which can help him if he requires it." Such observations motivate our hypothesis that risk pooling through social networks may vary within villages, with poorer individuals generally being more socially invisible and therefore enjoying less access to informal insurance than do wealthier, better connected individuals.

We define social invisibility as a condition in which an individual resides within a community but is not known by some minimal share of other members of that community. Toward this end, we define social visibility (*SV*) index. Let $\boldsymbol{N_i}$ be the number of times that respondent *i*'s name was drawn in the random matching process and presented to some other respondent *j*. Then let $n_i = \Sigma_j k_{ij}$ for $j=1,\ldots,N_i$, be the number of times that *i* was identified by others when presented as a random match ($k_{ij}=1$ when *j* knows *i*, $=0$ otherwise). We then estimate the social visibility index, *SV*, as:

$$SV_i = \frac{n_i}{N_i}, \qquad 0 \le SV_i \le 1 \tag{12}$$

The descriptive statistics on N_i, n_i and SV_i are presented in Table 3. Each individual was presented on average 5 times as a random match, out of which they were known on average by 3.38 respondents. 26 of the respondents (i.e., 8.39%) were not known by any of their random matches. Clearly they qualify as socially invisible by this metric. It turns out that, by this measure, *SV*=0 proves the statistically optimal maximum index value for denoting a respondent "socially invisible", with those with *SV*>0 classified as socially visible.[12]

Table 4 presents summary statistics on the individual characteristics for the socially visible and the socially invisible. Six key facts emerge from this table. First, the socially invisible are predominantly female (only 23% of them are male). Second, they are slightly younger than their socially visible counterparts. Third, a little more than half of them (54%) have been fostered, i.e., as a child they lived in the care of persons other than their parents and outside of their homes for at least a year. Fourth, far more of them were the first generation to reside in the village, 71 percent versus 39 percent among the socially visible. Fifth, fewer of them had parents who have held village offices. Finally, the socially invisible are poorer than their socially visible counterparts, with a mean non-land wealth value of 3.7 million Cedis as compared to 7.0 million Cedis for the socially visible.

These simple cross-tabulations are reinforced by a multivariate regression analysis. Let $l_{it}=1$ be an indicator variable that equals one if individual *i* is socially invisible at time *t*. Let $Pr\{l_{it}=1\}$ be the probability that $l_{it}=1$ conditional on some individual characteristics, X_{it}. We then estimate

$$Pr\{l_{it}=1\}=\Lambda(X_{it}\beta+\varepsilon_{it}>0) \tag{13}$$

by probit regression, where Λ is the normal CDF. We estimate a random effects model using all three rounds of data, with observations clustered on the respondent's identity.[13] We should note that in cross-sectional data, unobserved heterogeneity among respondents could well confound causal inference about the relationship between explanatory variables and the social invisibility indicator variable. However, in the present setting, our objective is merely to establish statistical associations between individuals' observable attributes and their social visibility in order to identify targetable

[12] More precisely, we estimated all the models reported below for different threshold values of SV to separate the socially visible and socially invisible, defining *Socially Invisible*=1 if *SV*≤ 0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35 and 0.40, with *Socially Invisible*=0 otherwise. The greatest likelihood value was achieved with the cutoff set such that the socially invisible had *SV*≤0 and the socially visible had SV>0..

[13] In principle, it would be more efficient econometrically to use an estimator (e.g., Tobit) for censored dependent variables. However, since in the next step we discretize the sample into two subsamples – the socially visible and the socially invisible – because the theory implies this approach – an estimator for dichotomous dependent variables (e.g., probit) becomes preferable here.

characteristics. Moreover, in the next section, where our interest is the causal relation between social visibility and individuals' ability to use social networks to insure themselves against risk, we control for unobserved heterogeneity using standard first-differencing techniques. We obviously cannot use that method here since individual attributes and social visibility do not change during the survey period.

The parameter estimates are presented in Table 5. The results reinforce the descriptive statistical results. Social invisibility is declining in age and wealth, is significantly less for those whose family has resided in the village for more than one generation and for those who are not farmers. This latter result is consistent with Santos and Barrett's (2004) results using these same data but a different model; they likewise find that teachers and traders are more likely to be known and the older are less likely to know the younger members of community. Belonging to a major clan reduces the likelihood of being socially invisible since one may establish links with members of ones' matrikin (Goldstein 1999, De Weerdt 2002, Santos and Barrett 2004, Udry and Conley 2005). On the other hand, having been fostered increases the likelihood of being socially invisible. In addition, having education beyond the middle school level increases the likelihood of being socially invisible. While this seems counterintuitive, De Weerdt (2002, p.12) found that "households with educated members tend to lie closer to each other on the network graph." By assortative matching, the relatively highly educated are thus more likely to be linked to each other and since they have fewer peers (i.e., those with higher than middle school education make up only 7.03% of the population) they appear less likely to be known by others. Moreover, the relatively highly educated may have left the village for a number of years in pursuit of education, thereby interrupting patterns of social interaction that condition social visibility. Being male, and having parents who held village offices were consistent in sign with the cross tabulations but not statistically significant, even at the 10% level.

The definition of social invisibility used thus far relies on reporting by a very small subsample – from 1 to 15 people – to whom each respondent's name was presented as a random match. This may generate small sample variability in the measure of social visibility. So we repeated the exercise, this time by estimating each individual's social connectedness as reflected in the pattern of k_{ij}, the indicator variable reflecting whether j

knows i. Now, rather than using k_{ij} directly to estimate SV_i as a function of the relatively few matches to which each individual's name was presented, N_i, we instead estimate a probit regression of k_{ij} to establish patterns of social visibility and then use those estimates to predict the probability of i being known by each sample respondent j.[14] Based on an optimally chosen cut-off value for that probability, we can then estimate SV_i over the whole village sample, N_v-1, for each respondent, substantially increasing the number of prospective social links over which social visibility is measured for each individual. We follow Santos and Barrett (2004) in this specification, allowing for asymmetry in who knows whom by controlling for the direction of prospective differences between a respondent and her match, not just the algebraic distance between them. For example, a non-teacher may indicate that she knows a random match who is a teacher, but the teacher might not know that respondent. Unlike in the insurance relationship, reciprocation is not necessary in individuals' awareness of one another.

The probit estimation results are presented in Table 6. Respondents who were both male, had the same level of education, had resided in the village for more than one generation and belonged to the same clan were more likely to know each other. Older, poorer respondents who were farmers or traders were more likely to be known. In addition, females were more likely to know males, males were more likely to know females and non-farmers were more likely to know farmers. On the other hand, farmers were less likely to know non-farmers, respondents who were fostered were less likely to know those who were not fostered and less likely to know each other.

Based on the results reported in Table 6, out-of-sample predictions were made to determine the likelihood of each individual being known by all sampled individuals in their village. We then set $\hat{k}_{ij}=1$ based on some minimum threshold probability, using 0.1 point intervals from 0.1 to 0.9. We then computed $\hat{SV}_i \equiv \Sigma_{Nv-1}\, \hat{k}_{ij}/(N_v\text{-}1)$ for each respondent based on these predicted probabilities and cut-off value. As before, we used different threshold values to discretize the resulting $\hat{SV}$ continuum into the socially invisible and the socially visible. For the predicted social visibility index, the maximum likelihood occurs when we let socially invisible=1 if $\hat{SV}_i \leq 0.25$ and 0 otherwise, for $\hat{k}_{ij}=1$

[14] We used the entire roster of individuals in the intra-village samples from wave 2.

if the predicted probability ≥ 0.8. By this definition, 22.79% of the sample was socially invisible, nearly three times as many as under the stricter SV_i=0 criterion used with the direct matching data. The bottom row of Table 3 compares the two social visibility indices computed by the direct and probabilistic imputation methods. The predicted social visibility continuum had a lower mean, 0.38 as compared to 0.67 for the index based on direct matches. On average, respondents were predicted to be less visible than previously indicated by the index based on random matches with a small sub-sample. The two social visibility indices were statistically significantly correlated at the one percent level with a correlation coefficient of 0.47.

But the real point is that there is considerable variation in social visibility even within relatively small rural villages. Clearly, not all residents within these rural Ghanaian villages are equally well known by others within the community. Some people appear sufficiently infrequently known by others that one might reasonably term them socially invisible. Does this matter to individual risk management capacity?

5. Risk Pooling Conditional on Social Visibility

If social connectedness fundamentally affects how an individual's expenditures vary with the shocks she experiences, as suggested by section 2's simple general equilibrium model of risk pooling, then conventional tests for risk pooling should condition on these measures of social (in)visibility. The relevant hypotheses differ between the socially visible – who are expected to pool risk – and the socially invisible – who are not.

Given the heterogeneity within these Ghanaian villages in social connectedness, as demonstrated in section 4, we hypothesize that global tests of risk pooling may mask heterogeneity in access to risk management through mutual insurance and related mechanisms. We use the agricultural, health, theft and mortality shocks discussed earlier as proxies for y_{inst}. This requires adaptation of equation (11), substituting change in the vector of shocks for the scalar $\Delta\tilde{y}_{inst}$ variable. The joint null hypothesis of full risk pooling remains unchanged (H_0^F: β=0, γ=1 versus H_A^F: β>0 or γ<1). We expect this to apply only to the socially visible subsample. The no risk pooling null hypothesis has to be adapted for the use of proxy variables, however. Thus we test H_0^N : γ=0 versus H_A^N : γ>0 and expect the null to apply to the socially invisible subsample only. The coefficient estimates on the shock variables should also be statistically significantly different from zero, indicating that individual-level consumption is directly affected by individual-level shocks, but the magnitudes of the relevant coefficients are indeterminate given the dummy variable nature of the shock indicators. Rejection of the former null via an F-test is strong evidence against full risk pooling, while rejection of the latter null via a t-test suggests at least partial risk pooling.

In order to generate results that are directly comparable to those in the existing literature, we first assess the extent to which any individual (visible or invisible) pools risk with other individuals in the village. Following equation (11), we regress the period-on-period change in individual private consumption expenditures on the period-on-period change in farm, health, theft and mortality shocks as well as the period-on-period change in residual village average consumption (i.e., excluding person *i*). We use a fixed effects estimator, clustering observations on the respondent's identity, with Huber-White robust standard errors. Table 7 shows that individual private consumption is not statistically significantly related to individual shocks and tracks village average consumption directly, albeit not one-for-one. A unit change in the village average consumption corresponds to only a 0.48 change in individual private consumption. This implies that individual consumption varies in response to shocks that affect village average consumption, implying some social insurance. While an F-test rejects the null hypothesis of full risk pooling, a t-test on the village average consumption also rejects the null of no risk pooling.

As seems the norm in the existing empirical literature on risk pooling in village economies, these data support a finding of partial risk pooling but reject the full insurance hypothesis when one pools all households. Such a finding could certainly be attributable to any of several well-known and quite plausible insurance contracting problems related to search, transactions costs, monitoring and enforcement, etc. (Fafchamps 1992, Murgai et al. 2002). The contribution of this paper is to offer a different, potentially complementary explanation of this familiar result. In particular, we hypothesize that global tests applied to all sample respondents may mask differences between subpopulations with different degrees of social connectedness, blending socially visible individuals who enjoy reasonably complete risk pooling with socially invisible individuals who have little or no access to risk pooling to manage idiosyncratic shocks.

To explore that hypothesis, we now disaggregate the data into two subsamples: socially visible and socially invisible individuals. We repeat the previous exercise for each subsample, now regressing change in individual level consumption for visible individuals on the change in their individual level shocks and the change in residual village average consumption (i.e., excluding the respondent) for other visible individuals.[15] We then repeat this regression using only socially invisible respondents. The results based on the direct elicitation method for determining social visibility are reported in the second and third columns in Table 7.[16]

The estimated partial correlation between changes in average consumption of visible individuals within the village and changes in individual consumption is more than 10 times greater for socially visible respondents than for socially invisible persons. Furthermore, the various shocks have no significant effect on individual private consumption even at the 10% level among the socially visible subpopulation. Their estimated magnitudes are smaller than in the pooled regression and much smaller than in the same regression applied to socially invisible individuals, for whom each shock variable is significant at the one percent level. Most notably, an F-test fails to reject the full insurance null hypothesis for the socially visible, even at the 20% level, but overwhelmingly rejects it for the socially invisible. Indeed, among the socially invisible, we cannot reject the no risk pooling null hypothesis even at the 20% percent level. Visible individuals appear to achieve something very close to full risk pooling with other

[15] Note that the theory does not imply a continuous relationship between SV and risk pooling. Although it might appear more efficient in econometric terms to let the risk pooling parameters vary with the continuous value of SV than to divide the sample into two distinct subsamples and estimate equation (11) separately for each, there is no reason to expect the effect of shocks to vary continuously across the distribution of SV. Hence our approach.

[16] The results based on the predicted social network structure method – classifying individuals as socially visible if SV_i>0.25 for k_{ij}=1 if the predicted probability ≥ 0.8, which yielded the greatest likelihood value – are available from the authors by request. These generate qualitatively similar results. The socially visible individuals enjoy full risk pooling at the village and network levels whereas the socially invisible are left uninsured. But because of the imprecision necessarily introduced by using imputed social networks, we favor the estimates based on directly elicited networks.

visible individuals in the village while socially invisible persons are left out of these arrangements and must self-insure against idiosyncratic shocks.[17]

By an order of magnitude, health and mortality shocks have the least effect on consumption of the socially invisible, followed by farm and theft shocks. The difference in the effects of the respective shocks may be attributed to a number of factors. For instance, tradition places more value on life than inanimate objects hence a theft, although considered unfortunate, is not viewed as crucial to survival and hence may not garner the same level of support as a health shock. Moreover, custom requires that one call on the sick and the bereaved.[18] The latter enforces some generalized reciprocity with regards to health and mortality shocks. Second, whereas a health shock is readily observable and verifiable, other than in extreme cases thefts and farm shocks may not be obvious to all others in the village. People do not assist with shocks they do not know happened. The directions of change as per the signs on the coefficients of shocks are mixed. Whereas an increase in the period-on-period change in mortality, farm and theft shocks is associated with a decrease in the corresponding individual private consumption expenditures, an increase in the period-on-period change in health shocks is associated with an increase in individual private consumption expenditures. Curiously, health shocks appear slightly overcompensated for by private consumption expenditures.

To this point, we have explored risk pooling at the village and within the village subpopulation that is similarly (in)visible. Since the data include information on social network structure, however, we can go one step further and repeat the risk pooling tests, but now assess the extent to which an individual pools risk with members of his/her social network by using the change in average consumption within the individual's social network, $\Delta\bar{c}_{nst}$, as the key regressor in place of the change in village average consumption. In using the directly elicited network based on random matching within

[17] We also tested for full risk pooling of visible individuals with all other individuals in the entire village. The results showed that visible individuals only partially pool risk with the entire village comprising both the socially visible and invisible. This is to be expected since by definition the visible do not have any social connections with the socially invisible in the village.

[18] It is customary for a sick person to send a message to friends and family informing them about his/her predicament. In addition, one has to go greet the bereaved and offer them drinks and/or cash towards the organization of the funeral. In the Akan tradition the latter is termed "*wo ko bo nsawa*" (translated as "going to give a donation towards the funeral").

sample, this analysis is obviously conditional on being visible since the optimal threshold for distinguishing the socially visible from the socially invisible using that measure was SV_i=0. We use the mean individual consumption for the known random matches as a proxy for network average consumption.

The point estimates in Table 8, with an intermediate estimate for γ of 0.92 and a standard error of 0.06, indicate that we can reject the no risk pooling null hypothesis at the one percent level. On the other hand we fail to reject the full insurance null hypothesis at conventional significance levels. The individual shock variables' coefficients are statistically insignificantly different from zero, with low magnitudes similar to those found in comparing socially visible individuals against all other socially visible individuals within the village.[19]

Finally, we assess the extent to which these respective networks pool risk with other networks in the village. The preceding analysis assumes implicitly that networks are segmented and thus that there is no spillover of insurance benefits from one network to another through one or more members common to multiple networks. However, interlinkages may enable networks to reinsure each other, such that *j*'s mutual insurance relation with two individuals, *h* and *i*, who do not know or directly interact with one another, effectively creates indirect (second-order) risk pooling among *h* and *i*. We can crudely test this hypothesis using the same method by taking the social network as a unit and regressing the change in each individual's social network average consumption on the change in network-level mean farm, health, theft and mortality shocks – thereby capturing the covariate element of shocks within the social network – as well as the change in residual average consumption for all networks in the village (i.e., excluding the current network). The results are given in Table 9.

Network average consumption statistically significantly comoves with village average consumption. Indeed, the point estimate is strikingly close to one, which would suggest perfect reinsurance if network average consumption were uncorrelated with average (i.e., covariate) shocks within the network. However, we do find that network

[19] The regression results from the predicted social network structure method were similar. We can reject the no risk pooling null hypothesis at the one percent level, with a γ of 0.80 and a standard error of 0.23. However, we fail to reject the full insurance null hypothesis, with F(5,297) =0.81 and Prob>F=0.5422. The individual shock variables were not statistically significantly different from zero.

average consumption statistically significantly covaries with expenditures related to health shocks within the network. We thus reject both the full and no risk pooling null hypotheses, although reinsurance among networks appears substantial in economic terms nonetheless. This only further underscores how social visibility is necessary for individuals to take advantage of informal risk pooling mechanisms available through social networks, including the reinsurance apparently available through network interlinkage.[20]

One important limitation of the foregoing analysis is that the data only permit us to study intra-village networks. Social networks may certainly cross village lines. In fact, it may be these 'weak ties' that serve the very purpose of spreading risk, e.g., social re-insurance, as in models of marriage markets that consider risk management incentives in the choice of a spouse for a child (Rosenzweig and Stark 1989). This remains a topic for future study, as the present data do not permit exploration of social linkages beyond the village.

Subject to that important caveat, our results corroborate previous studies' findings, using other data, that there is only partial risk pooling within rural villages. Unpacking this result by disaggregating the data according to the social visibility of individual respondents, however, shows that full risk pooling is achieved by visible individuals with other visible individuals both at village and network levels, with something very close to full risk pooling (i.e., reinsurance) among social networks within the village. On the other hand, the socially invisible fail to achieve risk pooling at any economically or statistically significant level. Table 10 summarizes these results.

6. Conclusions

Although risk management is crucial to rural households in low-income countries and the development studies literatures in economics and cognate disciplines are rich with descriptions of informal insurance arrangements, risk pooling through social

[20] The predicted social network structure method yields qualitatively similar results. We reject the full risk pooling null hypotheses. However, the coefficient on the village average consumption was much lower, 0.023 as compared to 1.021 in the direct matching regression. In addition, we can only reject the no risk pooling null hypothesis at the 10% level.

networks may not be universally available for the simple reason that not everyone is socially well connected. The simple general equilibrium theory of risk pooling implies that individuals who are socially visible within networks will enjoy the consumption smoothing benefits of mutual insurance while those who are socially invisible will not. If villages include both types of individuals, then tests of the extent of informal insurance based on regressions that pool both sorts of individuals can lead to biased, intermediate results suggesting partial risk pooling, as is typical of the literature.

This paper identified a minority subpopulation of socially invisible individuals in rural Ghana who are not widely known – in extreme cases, not known at all – by other residents within their villages. In particular, we find that poorer, younger residents who farm, do not belong to a major clan, have been fostered and have resided in the village for only one generation are most likely to be socially invisible. Estimating now-standard Townsend-style regressions, we obtain the usual, partial risk pooling result when we fail to separate the sample into socially invisible and socially visible subpopulations. Once we separate the sample, however, we cannot reject the full risk pooling null hypothesis for socially visible individuals, nor can we reject the no risk pooling hypothesis for the socially invisible. Thus in these data, village-level tests for complete mutual insurance appear to represent a mixture model that generates misleading results of universal partial risk pooling when the reality seems more socially variegated, with a socially invisible minority of the population having little access to social networks-mediated risk management, while most of the population enjoys something economically and statistically close to complete pooling of idiosyncratic risk. Moreover, for those in social networks, interlinkages among social networks appear to provide quite effective reinsurance against network-level covariate risk that is idiosyncratic within the village.

In summary, this study corroborates a vast literature that finds many individuals in rural villages use social networks to effectively insure themselves against idiosyncratic risk, while also accommodating an oft-overlooked literature on social exclusion and social invisibility within rural villages that suggests insurance coverage is likely uneven among individuals. Within-village variation in social connectedness, like within-village variation in wealth and other attributes, appears to have a profound effect on risk management capacity.

In policy terms, empirical evidence of Pareto efficient allocation of idiosyncratic risk among socially visible members of networks suggests that given binding budget constraints, interventions should target primarily (i) village-level (or larger-scale) covariate risk that is inherently uninsurable through social networks and (ii) idiosyncratic shocks faced by those left out of these networks (i.e., the socially invisible). This implies a need for careful identification of who is socially well-connected and who is not, paying particular attention to the latter subpopulation for the purposes of targeting interventions that might stitch up the holes in extant social safety nets. Such targeting can be difficult. Our results offer some preliminary empirical insights on who is more or less likely to be socially invisible within these particular villages; but one would need to study this more directly in order to design a reliable targeting strategy. Once such targeting methods have been worked out properly, assistance might take the form of either direct interventions to provide (quasi-)insurance to socially invisible persons, or efforts to improve the social integration of individuals most likely not to be well-connected socially (e.g., recent migrants into a community). Given our finding that young farmers who are relatively recent settlers in a community are most likely to be socially invisible, this might suggest possibilities involving quasi-insurance built into agricultural credit, product sales or input delivery contracts with certain demographic subgroups as an indirect means of insuring this subpopulation. Greater effort needs to be made to identify and reach the socially invisible, lest they fall through the apparent holes in otherwise well-functioning social safety nets.

Table 1: Individual consumption expenditures, June 2004- January 2005 (nominal Cedis per month)

Village	Round 1			Round 2			Round 3		
	Mean	Standard Deviation	Share of Total Expenditure	Mean	Standard Deviation	Share of Total Expenditure	Mean	Standard Deviation	Share of Total Expenditure
1	378033	361238	0.190	389513	374807	0.244	607648	1952393	0.235
2	615055	1166220	0.189	363188	438698	0.209	373984	333596	0.220
3	442872	1894519	0.117	258599	375004	0.151	359117	1721446	0.131
4	171599	137713	0.126	228730	415352	0.144	188596	210620	0.134
Full Sample	393383	1097788	0.156	306422	404741	0.185	379544	1334326	0.178

Table 2: Percentage of individuals affected by shocks and mean response expenditure/ imputed value of damage (nominal Cedis)

Shocks	All Rounds	Round 1			Round 2			Round 3		
	Frequency	Frequency	Mean	Share of Total Expenditure	Frequency	Mean	Share of Total Expenditure	Frequency	Mean	Share of Total Expenditure
Farm problems	31.7	52.0	1107214	0.512	22.8	304984	0.238	20.6	200643	0.133
Total Health Expenses	56.7	72.2	1699291	0.580	50.0	379575	0.513	46.0	307786	0.286
Theft of personal item	14.7	19.1	768218	0.405	13.7	381595	0.203	11.0	365600	0.390
Sudden death	50.7	50.5	880862	0.459	55.9	171809	0.125	45.6	228589	0.109
Any/All Shocks	84.6	91.8	2640621	1.093	83.0	492290	0.494	78.7	415992	0.319

Table 3: Summary statistics on random matching

Variable	Mean	Median	Min	Max
Number of times presented as a match (*N*)	5.00	5.00	1	15
Number of times known as a match (*n*)	3.38	3.00	0	13
Social visibility (*SV*) index – direct matches	0.67	0.75	0	1
SV index – imputed matches*	0.38	0.32	0	1

* Based on an optimal cut-off level of 0.80 predicted probability of *i* being known

Table 4: Descriptive statistics

Variable	Definition	Frequency (%)		
		Entire Sample	Socially Visible	Socially Invisible
Male	=1 if male, 0 otherwise	47.6	49.5	22.9*
Age	Respondent's age	45.5 (12.9)	45.9 (13.1)	40.8* (9.4)
Level of Schooling				
No schooling	=1 if respondent has no schooling, 0 otherwise	25.2	25.1	25.7
Primary School	=1 if primary level, 0 otherwise	17.0	16.6	22.9
Middle School	=1 if middle school or junior secondary school, 0 otherwise	50.8	51.2	45.7
Higher School	=1 if any higher, 0 otherwise	5.7	5.7	5.7
Occupation				
Farmer	=1 if farmer, 0 otherwise	78.9	78.8	80.0
Other	=1 if trader, artisan, teacher, civil servant, office or health worker, agricultural or non-agricultural labor, 0 otherwise	17.8	18.9	14.3
Unemployed	=1 if student/ pupil, unemployed or not in the labor force	3.3	3.1	45.7
Major clan	=1 if member of a major clan, 0 otherwise	89.8	90.2	84.3
Herelong	=1 if not the first generation to reside in village, 0 otherwise	59.1	61.4	28.6*
Parents held office	=1 if parents holds any village office, 0 otherwise	47.1	48.1	31.3*
Fostered	=1 if respondent was fostered, 0 otherwise	53.7	53.6	54.3
Value of non-land wealth	Value of esusu, bonds, pension, jewelry, cash being kept with others, chemicals, seeds, crops and goods to be traded in millions of Cedis	6.7 (9.2)	7.0 (9.5)	3.7 (3.8)
Value of inheritance	Total value of any current and expected land and non-land inheritance in hundred millions of Cedis	92.2 (1656.4)	99.2 (1718.7)	0.2 (0.6)
Location				
Village 1	=1 if Village cluster 1, 0 otherwise	25.8	26.7	14.3*
Village 2	=1 if Village cluster 2, 0 otherwise	22.9	24.3	4.3*
Village 3	=1 if Village cluster 3, 0 otherwise	24.3	21.8	57.1*
Village 4	=1 if Village cluster 4, 0 otherwise	27.0	27.2	24.3

Notes: * Differences in means statistically significant at the 5% level. The standard deviations of continuous variables are given in parentheses.

Table 5: Probit estimation of social invisibility

Variables	Marginal Effects	Standard Error	Prob>|z|
Dependent Variable: Socially invisible (*SV*=0)			
Individual Characteristics			
Male	-0.123	0.226	0.587
Age	-0.027*	0.009	0.004
No schooling	-0.298	0.252	0.237
Primary school education	0.284	0.215	0.187
Higher than middle school	0.655**	0.329	0.046
Non-farm occupation	-0.605***	0.343	0.077
Unemployed	0.605	0.457	0.185
Assets			
Value of non-land wealth	-0.067**	0.032	0.037
Value of inheritance	-0.103	0.106	0.330
Social characteristics			
Major clan	-0.576**	0.230	0.012
Herelong	-0.292***	0.178	0.100
Fostered	0.650**	0.228	0.004
Parents held office	-0.077	0.178	0.665
Location			
Village 2	-0.240	0.344	0.485
Village 3	1.255	0.270	0.000
Village 4	0.532	0.268	0.047
n = 852			
Log likelihood = -144.54			
Wald $\chi^2(16) = 67.59$, p-value = 0.000			

Notes: ***, **, * Significant at the 1%, 5% and 10% levels, respectively.
Comparison group is a female respondent from village 1 who farms and has a middle school education.

Table 6: Probit estimation of the likelihood of knowing a random match

Variables	Definition of variables (i=respondent, j= -i intra-village sample individual)	Marginal Effects	Prob>|z|
Both male	=1 if both i and j are male, 0 otherwise	1.030***	0.000
Female, male	=1 if i is female and j is male, 0 otherwise	0.394***	0.000
Male, female	=1 if i is male and j is female, 0 otherwise	0.200**	0.029
Older	=1 if i is older than j, 0 otherwise	0.152**	0.024
Same education	=1 if both i and j have the same level of education, 0 otherwise	0.213***	0.000
Same occupation	=1 if both i and j have the same occupation, 0 otherwise	-0.119	0.230
Trader, non-trader	=1 if only i identifies himself as a trader, 0 otherwise	-0.375	0.131
Non-trader, trader	=1 if only j identifies himself as a trader, 0 otherwise	0.207	0.121
Farmer, non-farmer	=1 if only i identifies himself as a farmer, 0 otherwise	-0.527***	0.000
Non-farmer, farmer	=1 if only j identifies himself as a farmer, 0 otherwise	0.542***	0.000
Same clan	=1 if both i and j belong to the same clan, 0 otherwise	0.245***	0.001
Both herelong	=1 if both i and j have resided in the village for more than one generation, 0 otherwise	0.327***	0.001
Herelong, not-herelong	=1 if only i has resided in the village for more than one generation, 0 otherwise	0.012	0.913
Not-herelong, herelong	=1 if only j has resided in the village for more than one generation, 0 otherwise	0.061	0.562
Both fostered	=1 if both i and j have been fostered, 0 otherwise	-0.291**	0.004
Fostered, not-fostered	=1 if only i has been fostered, 0 otherwise	-0.317**	0.004
Not-fostered, fostered	=1 if only j has been fostered, 0 otherwise	0.032	0.762
Poorer	=1 if i is poorer than j, 0 otherwise	0.111**	0.054
Age	Age of i	0.003	0.323
Value of nonland wealth	Value of non-land wealth owned by i, millions of Cedis	0.000	0.433
Farmer	=1 if i identifies himself as a farmer, 0 otherwise	0.723***	0.000
Trader	=1 if i identifies himself as a trader, 0 otherwise	0.776**	0.003
Village 2	=1 if i lives in village 2, 0 otherwise	0.187*	0.094
Village 3	=1 if i lives in village 3, 0 otherwise	-0.754***	0.000
Village 4	=1 if i lives in village 4, 0 otherwise	-0.199*	0.055

n=3724
Log likelihood = -1952.09
Wald chi2(25) = 342.66
Prob>chi2 = 0.000

Notes: ***, **, * Significant at the 1% , 5% and 10% levels, respectively.

Table 7: Regression tests for full and no risk pooling

Dependent variable: Change in individual private consumption expenditure

	All Individuals		Visible Individuals		Invisible Individuals	
	Coefficient	Robust Standard Error	Coefficient	Robust Standard Error	Coefficient	Robust Standard Error
change in loss due to farm problems	-0.056	0.045	-0.012	0.022	-0.872***	0.110
change in total health expenses	0.002	0.002	0.001	0.001	0.020***	0.001
change in theft of personal item	0.029	0.039	-0.008	0.015	-0.979***	0.099
change in expenses due to sudden death	0.004	0.008	0.002	0.007	-0.614***	0.077
change in residual village average consumption	0.483***	0.226	0.564***	0.268	-0.042	0.123
constant	-9691.782	56172.990	-10796.500	67423.300	-39829.600***	42733.190
Joint test for full risk pooling	F(5, 301) =2.10, Prob>F=0.07		F(5, 257) =1.42 , Prob>F=0.22		F(5, 12) =223.6, Prob>F= 0.00	
	n=649		n=597		n=52	
	R^2=0.010		R^2=0.007		R^2=0.193	

Notes: ***, **, * Significant at the 1% , 5% and 10% levels, respectively.

Table 8: Risk pooling for an individual in his/her directly elicited social network
Dependent variable: Change in individual private consumption expenditure

	Coefficient	Robust Standard Error
change in loss due to farm problems	-0.009	0.019
change in total health expenses	0.001	0.002
change in theft of personal item	0.015	0.022
change in expenses due to sudden death	0.005	0.009
change in residual network average consumption	0.920***	0.059
constant	-106935.100	102756.000

Joint test for full risk pooling: $F(5, 257)=0.47$, $Prob>F = 0.80$
n=597
R^2=0.750

Table 9: Insurance among social networks within a village
Dependent variable: Change in network average consumption expenditure

	Coefficient	Robust Standard Error
change in loss due to farm problems	0.001	0.013
change in total health expenses	0.002***	0.001
change in theft of personal item	0.004	0.011
change in expenses due to sudden death	0.004	0.005
change in residual village average consumption	1.021***	0.244
constant	-3083.776	32233.200
Joint test for full risk pooling: F(5, 265) = 28.67, Prob>F = 0.00		
n=597		
R^2=0.055		

Table 10: Summary of results for tests for risk pooling

	Full Risk Pooling	No Risk Pooling	Inference
An individual in a village	Rejected	Rejected	Partial risk pooling
A visible individual in a village	Not rejected	Rejected	Full risk pooling
An invisible individual in a village	Rejected	Not rejected	No risk pooling
An individual in a network	Not rejected	Rejected	Full risk pooling
A network in a village	Rejected	Rejected	Partial reinsurance

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