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An Empirical Analysis of Health Shocks and Informal Risk Sharing Networks

Andinet Woldemichael and Shiferaw Gurmu*

***Abstract*:** Using panel household survey data from rural Ethiopia, we investigate informal risk sharing against health shocks in the presence of multiple risk sharing networks. We find that neither short-term nor long-term health shocks are insured through transfers from networks such as friends, neighbors, and members of informal associations. However, networks related along bloodline such as extended family members provide assistance when health shocks are long-term such as disabilities. The results show that these networks strategically complement planned component of their transfers which are made on a regular basis such as remittance, entitlement, or chop money (small cash sums for household expenses). Moreover, we find significant history dependence in transfers from not only genetically distant networks but also extended family members as well as formal institutions, which seems to discourage dependency. Finally, the findings suggest significant heterogeneity in transfers.

1. Introduction

Risks and shocks are fundamental to the creation and reproduction of poverty. Not only do they reduce current consumption levels but also welfare by reducing the ability of households to cope with subsequent shocks (Fafchamps, 1999). Health shocks are the most important idiosyncratic risks that people in rural areas face. In the absence of formal insurance markets and public insurance systems, poor households in low-income countries are forced to devise their coping strategies. One such strategy is participation in informal risk sharing arrangements which are voluntary contracts in which individuals provide assistance to others in exchange for a credible promise of future reciprocity. In this paper, we investigate the extent to which informal risk sharing arrangements insure health shocks in the presence of multiple and overlapping risk sharing networks. Using panel household survey data from rural Ethiopia, we assess how transfers from different risk sharing networks with heterogeneous motives, including formal institutions respond to health shocks. Moreover, we probe whether there is strategic interaction—complementarity or substitution—among networks, and if so to what extent it determines households' ability to cope with health shocks.

Like many other low-income countries,[1] people in rural villages in Ethiopia have limited access to formal health insurance products against health shocks. Insurance markets in general and health insurance in particular are largely missing and tax-based public insurance systems and social protection programs are not accessible for the majority of people who earn a subsistence level of income from agriculture and informal sector activities. Subsidized health insurance programs, such as a community-based health insurance program, are only recent initiatives and are at very early stages of piloting and implementation. Gurmu and Tesfu (2011) provide details about the health care system of Ethiopia. For instance, the percentage of people covered by health insurance in 2011/2012 was only 1.13 per cent in rural areas and 2.47 per cent in urban areas, a slight increase from 0.32 per cent in 2007/2008 (FMoH, 2014). Consequently, health shocks are largely absorbed by the individual herself, often with support from informal social networks such as relatives, friends, and neighbors. The extent to which these networks provide some level of cushion against health shocks—short-term or long-term—is not well understood, particularly in the presence of overlapping social networks.

Our study contributes to the literature by empirically investigating how informal risk sharing through transfers from different networks responds to health shocks. We conduct the analysis separately for short-term and long-term health shocks, assessing

*Andinet Woldemichael, African Development Bank Group, Avenue Joseph Anoma, 01 BP 1387 Abidjan 01, Côte d'Ivoire; e-mail: a.woldemichael@afdb.org. Shiferaw Gurmu (corresponding author), Department of Economics, Andrew Young School of Policy Studies, Georgia State University, Atlanta, GA 30303; e-mail: sgurmu@gsu.edu.

risk sharing against transitory illnesses versus long-term shocks, such as disabilities. The data comes from four rounds of Ethiopian Rural Household Survey (ERHS) panel data, covering about 1,480 households in 15 rural villages between 1994 and 1997. We consider transfers from different social networks, including family members, relatives, friends, neighbors, and members of informal savings, credit and funeral associations as well as formal religious, government and non-government organizations. Based on genetic proximity (along bloodline) to a household, we consider all possible networks which have made cash or in-kind transfers to the household.

The dependent variable is cash or in-kind transfer, with large proportion of zeros which arise due to either a corner solution where individuals decide to make zero transfers or transfers are not in the choice set. Using Dynamic Correlated Random Effects Seemingly Unrelated Regression (DSUR) Probit and Tobit models, we address issues of non-linearity in the distribution of transfers, state dependence, unobserved individual heterogeneity, and initial conditions problem. Moreover, the DSUR models allow for transfers from one network to be correlated with the other, providing important evidence on the extent and direction of interactions between social networks. The approach captures the interactions among networks not only on the time-varying idiosyncratic components but also on the time-invariant components of transfer. While the former can be interpreted as unplanned transfers made in response to unforeseen events or idiosyncratic shocks, the latter can be interpreted as planned transfers made on a regular basis, such as remittances, entitlement, and chop money (small cash sums for household expenses). In implementation, we use the hierarchical Bayesian estimation method with Markov Chain Monte Carlo (MCMC) simulation and data augmentation techniques to estimate the models.

To preview our results, we find that close family members and relatives, who are more likely to be altruistic along bloodline, make transfers in response to health shocks, particularly in response to long-term health shocks. The same network makes higher amount of transfers to households headed by older individuals, suggesting the importance of altruism motives or social norms in that support is provided today without anticipating future reciprocity. However, we do not find evidence of risk sharing against short-term and long-term health shocks from more distant social networks along bloodline, such as friends, neighbors, and fellow members of informal savings, credit, and funeral associations. Finally, we find significant history dependence in transfers from not only genetically distant networks but also extended family members as well as formal institutions.

The remaining part of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data. While Section 4 discusses the empirical strategy employed to estimate the model, Section 5 discusses results, and Section 6 concludes the paper.

2. Review of the Literature

It is well established that the Pareto optimum could be achieved through informal risk sharing contracts among self-interested but risk-averse individuals even in the absence of formal insurance institutions (Kocherlakota, 1996; Fafchamps, 1999; Ligon *et al*., 2002). Indeed, empirical evidence supports the existence of at least partial risk sharing against idiosyncratic income and consumption shocks (Morduch, 2002; Udry, 1994). However, there is little or no evidence of risk sharing among self-interested individuals against health shocks. Fafchamps and Lund (2003) find that while income shocks are insured through risk sharing arrangements in rural Philippines, acute and non-acute health shocks are not. Similarly, a study from rural Tanzania finds no evidence of risk sharing against health shocks at social network and village levels (De Weerdt and Dercon, 2006).

However, motives other than self-interest, such as emotions, are also important aspects of risk sharing because for sufficiently large motives, the voluntary participation constraint becomes irrelevant and individuals help each other without the anticipation of future reciprocity (Fafchamps, 2011). As discussed in Fafchamps (2011), altruism is the most important emotion in the context of risk sharing, which is understood as a strong emotional reward from helping others and can potentially serve as an enforcement instrument for informal risk sharing arrangements. Altruism along bloodline, clan, and religious affiliations are by far the most important motives for risk sharing (Fafchamps, 2011; De Weerdt and Fafchamps, 2011; Fafchamps and Lund, 2003). In this regard, Dercon and Krishnan (2002) find that except for poor households in the southern region of Ethiopia, there exists risk sharing against illness shocks within households in that altruism along bloodline is stronger.

Furthermore, motives arising from social norms and customs are well recognized in determining individuals' sharing decisions (Fafchamps, 2011; Ligon and Schechter, 2012; Barr and Stein, 2008). These motives include fairness, inequality aversions, and redistributive social norms, which could be intrinsic, such as individuals' 'other-regarding preference' or extrinsic due to a system of rewards and punishments instituted by society. Empirical studies in this strand of the literature include Morsink (2014) using field experiment in Ethiopia, and Barr and Stein (2008) using funeral attendance in Zambia. In a Ghanaian village, Vanderpuye-Orgle and Barrett (2009) found that social connectedness play an important role in risk sharing where 'socially visible' individuals insure consumption shocks but not among 'socially invisible' subpopulation of the young, the poor, and so on.

Given that risk sharing could take place at various levels—within a household, a network, a village, an ethnic group, and a region—which are often overlapping, strategic interactions among them could determine the extent to which risks are efficiently shared. The interactions among these networks could be complementary or crowding out. Although there is a growing body of literature, such as Genicot and Ray (2003) and Fafchamps and Gubert (2007), the implications of strategic interaction in risk sharing in overlapping and endogenously formed networks on welfare is not well understood. In this regard, Boucher and Delpierre (2014) find that formal insurance such as index-based insurance schemes could crowd out informal risk sharing contracts, if such insurance is provided to individuals. Similarly, Lin et al. (2014) show that, in a laboratory experiment, formal insurance significantly crowds out informal risk sharing contracts and the loss in welfare due to crowding out is exacerbated in the presence of altruism and inequality. The implications of strategic interactions among social networks in providing insurance against idiosyncratic health shocks, however, are not well understood. This paper addresses these issues in the context of household survey panel data from rural Ethiopia.

3. Data and Descriptive Statistics

The study uses longitudinal data from the ERHS[2], one of the longest running household panel surveys in Africa. Started in 1989, the original survey includes seven villages. In this paper, we use the first four rounds collected in the 1990s, that is, the 1994a, 1994b, 1995, and 1997 rounds, covering 15 peasant associations (PAs) in four regions and approximately 1,480 households. The four waves provide a balanced panel with minimal attrition rate of around 6.7 per cent. The data have detailed information on households' demographic characteristics, consumption, health conditions, shocks, incomes, farming activities, informal networks, and transfers.

The dependent variable is cash or in-kind transfers that households received in the past four months. In implementation, we use the logarithm of transfers plus 1 to avoid finding log of zeros. In-kind transfers are converted to monetary values using local commodity prices collected in each survey year. The main explanatory variables measuring short-term and long-term health shocks are household head's number of physical disabilities and the number of days ill and unable to work in the past four months. In our empirical specifications discussed below, we include the difference between these two health measures and the corresponding village averages. A respondent is asked if he/she has (1) *difficulty to stand up from a seated position*, (2) *difficulty to sweep a floor*, (3) *difficulty to walk independently for 5 km*, (4) *difficulty to carry 20 liters for 20 meters*, and (5) *difficulty to hoe a field in the morning*. Our formal regression analysis controls for income and wealth using land size, the value of livestock owned and the logarithm of non-food expenditure as proxies. In addition, we include education to control for investment in health, health behavior, and household's performance in the local labor market. Other sets of control variables include demographic characteristics such as household size, marital status, and sex.

Table 1 show that about 21 per cent of households received transfers from different senders. However, the bulk of transfers come from benevolent institutions such as churches, mosques, government, and non-governmental organizations supporting more than two-third of the recipients or 13.8 per cent of households in the survey. This highlights that for many households in rural Ethiopia, aid from formal institutions is an important means of coping with shocks. The remaining 40 per cent of transfers come from informal sources such as non-resident family members, relatives, friends, neighbors, members of informal saving and credit (*Iqqub*) and funeral (*Iddir*) associations. The conditional average transfer was about 478 Ethiopian Birr, which was equivalent to 75.6 USD in 1994 exchange rate. When transfers are disaggregated by group, the amount of transfer from network Group I (non-resident family members), Group II (relatives), Group III (friends, neighbors, members of *Iqqub* and *Iddir*), and Group IV (church, mosque, NGOs, government organizations) are 341 Birr, 324 Birr, 141 Birr, and 562 Birr, respectively.

Table 2 presents descriptive statistics of the variables. On average, a household head is unable to work for eight days in a year due to illnesses. Conditional on being ill and unable to work, he/she loses about 36 work days in a year. With regards to long-term health shocks, about 26 per cent of household heads reported to have at least one physical disability, and out of the five indicators, the average number of disabilities is 0.7.

Table 1: Amount of annual conditional transfers received (in birr), (1994–1997)

Sender type	No. of obs.	Mean	Std. Dev.	Min	Max
Proportion of households who received transfers from:					
Any sender	5,803	20.66%			
Sender Group I	5,803	1.24%			
Sender Group II	5,803	4.10%			
Sender Group III	5,803	2.77%			
Sender Group IV	5,803	13.75%			
Conditional amount received from:					
Any sender	1,199	478	715	0	8,301
Sender Group I	72	341	254	24	1,155
Sender Group II	238	324	406	2	2,250
Sender Group III	161	141	118	12	800
Sender Group IV	798	562	816	0	8,301

Note: Birr is the local currency in Ethiopia. The exchange rate for 6.32 Birr/USD in 1994 and 7.06 Birr/USD in 1997/1998 (National Bank of Ethiopia). Sender groups: I. Non-resident family members, II. Relatives, III. Friends, neighbors, members of *Iqqub* and *Iddir*, and IV. Church, mosque, NGOs, government organizations.

4. Econometric Strategy

The empirical models are based on the theory of informal risk sharing strategies with limited commitment with voluntarily participation in anticipation of future reciprocity. Such an arrangement results in Pareto-optimal allocation among non-altruistic self-interested individuals (Kocherlakota, 1996). Altruistic motive, however, relaxes the participation constraint, with assistances provided without the anticipation of future reciprocity given that such motive is strong (De Weerdt and Fafchamps,

Table 2: Variables description and summary statistics

Description	Mean	Std. Dev.	Min	Max
Disabilities and illnesses:				
No. of disabilities of household heads (0/5)	0.731	1.414	0	5
No. of days household head was unable to work due to illness	1.998	5.945	0	30
Demographic characteristics and assets:				
Household size	5.911	2.969	1	25
Household head is male (1 = male, 0 otherwise)	0.775	0.418	0	1
Age of household head	47.07	15.87	15	100
Household head is married: (1 = married, 0 otherwise)	0.749	0.434	0	1
Log of non-food expenditure	3.72	1.283	0	7.818
Household head's education: Primary (1–6 Grade)	0.428	0.495	0	1
Household head's education: Junior High (7–8)	0.028	0.166	0	1
Household head's education: High school and above ($\geq$9)	0.032	0.177	0	1
Size of land (hectare)	1.338	1.418	0	13.38
Log of value of livestock	5.747	3.045	0	11.25
No. of observations by survey year:				
Round 1: March–July 1994	1,475			
Round 2: Sept. 1994–Jan. 1995	1,464			
Round 3: March–June 1995	1,460			
Round 4: June–Nov. 1997	1,404			
Total no. of observations	5,803			

Note: Number of disabilities is the sum of the following conditions: (1) difficulty to stand up from seated position, (2) difficulty to sweep a floor, (3) difficulty to walk independently for 5 km, (4) difficulty to carry 20 liters for 20 meters, and (5) difficulty to hoe a field in a morning.

2011; Fafchamps, 2011). Details of the conceptual framework of informal risk sharing with limited commitment, which is the basis for our empirical model, are available in a Supplementary Appendix A.[3]

4.1 The Benchmark Model

In the data, transfers are reported at a recipient household level. Using information on recipient household relation with the senders, we categorize transfers originating from four social network groups. We then estimate a recipient-level regression in a SUR framework allowing for interaction between networks. Because risk sharing contracts with limited commitment are inherently dynamic due to history dependence, we include the lagged value of the dependent variable as a regressor. The dynamic model of transfer from social network j to household i can be written as

$$\tau_{jit} = \gamma\tau_{ji,t-1} + \beta_1 HS_{it} + \beta_2 Age_i + \boldsymbol{\beta}_k \boldsymbol{x_{it}} + \alpha_{ji} + \varepsilon_{it}, \tag{1}$$

where τ_{jit} is the level of transfer household i receives in period t, HS_{it} is the difference between health shock experienced by the household head and the village average, and Age_i is the difference between household head's age and the village average capturing biological survival rate. Furthermore, $\boldsymbol{x_{it}}$ is a vector of control variables, ε_{it} is the error term which is assumed *i.i.d.,* $\{\gamma, \boldsymbol{\beta}\}$ are vectors of coefficients, and α_i is household specific intercept capturing unobserved individual heterogeneity. In the presence of limited commitment, γ is expected to be negative. Following the literature, we consider the village as partner and include the difference between household income and the village average.

Estimating dynamic unobserved effects model in Equation 1 involves a number of challenges, including an initial conditions problem, interdependence of transfers among different groups, and censoring in transfer amount due to corner solutions. We implement a dynamic correlated random effects (RE) model, which also makes estimating non-linear models such as Probit and Tobit models much simpler. In order to control for the correlation between the unobserved individual effects and the covariates, we follow Wooldridge's (2005) approach and include time-means of selected time-varying variables and the first round transfer amount in the model. This approach addresses the initial conditions problem and provides consistent estimates when the unobserved individual heterogeneity is correlated with some of the time-varying covariates.

Censoring due to corner solutions is another important issue in our case which arises due to substantial 'pile-up' of transfer amounts at zero. In our data, transfers are zeros for 80 per cent of the observation in the pooled sample and when disaggregated by group, the percentage increases to more than 90 per cent. Censoring could result in exaggerated slope estimates, commonly referred to as 'expansion bias', especially on the lagged value (Rigobon and Stoker, 2007). Finally, we also address the potential feedback effect from transfers to health shocks. One possible channel is past transfers affecting the chances of realizing health shocks in the current period though the direction is ambiguous. Since our dynamic specification directly controls for past transfers, potential feedback effects/endogeneity are less of an issue.

4.2 Risk Sharing with Strategic Interaction between Social Networks

The proposed benchmark model, which parsimoniously addresses the empirical issues discussed above, is a single-equation model that does not allow for strategic interaction of transfers from different social networks. We now present a DSUR model that addresses all empirical issues discussed above as well as possible strategic interaction among social networks. Let m denote sender group, where $m = 1$ indicates transfers from non-resident family members (Group I), $m = 2$ indicates transfers from a relative (Group II), $m = 3$ indicates transfers from a friend, a neighbor, or members of *Iqqub* or *Iddir* (Group III), and $m = 4$ indicates transfers from benevolent institutions such as church, mosque, government, or non-government aid organizations (Group IV). Then, the hierarchical Bayesian correlated RE DSUR Tobit model can be written as follows

$$\tau^*_{mit} = \gamma\tau_{mi,t-1} + \boldsymbol{X}_{mit}\boldsymbol{\beta}^m + \alpha_{mi} + \varepsilon_{mit}, \tag{2}$$

$$\tau_{mit} = max\left(\tau^*_{mit}, 0\right),$$

where τ_{mit} is the logarithm of transfer from sender group $m = \{1, 2, 3, 4\}$, τ^*_{mit} is the latent value of transfer, $\boldsymbol{X}_{mit}$ is a vector of covariates, α_{mi} is the unobserved individual effect, and ε_{mit} is the idiosyncratic error term. In addition, the random effects are assumed to be normally distributed conditional on a linear function of time-means of time-varying covariates ($\boldsymbol{X}_{mi}$) and the initial period log transfer (τ_{mi0}) and can be written as follows:

$$\alpha_{mi} = \delta\tau_{mi0} + \boldsymbol{X}_{mi}b^{m} + u_{mi}, \tag{1}$$

$$\boldsymbol{\varepsilon}_{it} = [\varepsilon_{1it}, \varepsilon_{2it}, \varepsilon_{3it}, \varepsilon_{4it}]|\alpha_{mi}, \boldsymbol{X}_{mit}, \tau_{mi,t-1} \sim N(0, \boldsymbol{\Omega}), \tag{2}$$

$$\boldsymbol{u}_{i} = [u_{1i}, u_{2i}, u_{3i}, u_{4i}]|\tau_{i0}, \boldsymbol{X}_{i} \sim N(\boldsymbol{u}, \boldsymbol{\Sigma}), \tag{3}$$

where $\boldsymbol{X}_i = (\boldsymbol{X}_{1i}, \boldsymbol{X}_{2i}, \boldsymbol{X}_{3i}, \boldsymbol{X}_{4i})$. The interdependences among different sender groups are captured through correlations among the idiosyncratic error terms and correlations among the unobserved individual heterogeneity terms, that is, off-diagonal elements of Ω and Σ, respectively, and are M $\times$ M.

We implement a hierarchical Bayesian estimation procedure, with data augmentation technique and MCMC simulation technique (Albert and Chib, 1993). Details of the estimation algorithm are given in a Supplementary Appendix B (see endnote 3). We also estimate RE DSUR Probit model as an alternative using dummy variable indicating receipt of transfers.

5. Results and Discussions

In this section, we discuss the main findings on risk sharing against health shocks, history dependence (limited commitment), and interdependence of transfers among networks of different social distances, and heterogeneity. Some of the tables and figures discussed below are given in a Supplementary Appendix C (see endnote 3).

The coefficient estimates for the dynamic Tobit model is given in Table C.1 of Supplementary Appendix C (see endnote 3). Tables C.2 and C.3 in Appendix C present the average partial effects (APEs) from static RE SUR Probit and Tobit models. While columns (i) and (ii) show the results when short-term and long-term health shocks enter the model separately, column (iii) presents the results when both enter the model. The results (APES) from the dynamic version of the models are given in Tables 3 and 4.

5.1 Health Shocks and Risk Sharing

The results from the static and the dynamic models show that transfers from different sender groups are not responsive to short-term health shocks. This holds true regardless of social distances and model specifications. Although the APEs are positive in the dynamic Tobit model (Table 4, column (i)), it becomes statistically insignificant when we include long-term health shock in the model (column (iii)). Furthermore, not only the APEs are statistically insignificant but the magnitudes are also economically insignificant. This implies that regardless of social distances, households in rural Ethiopia do not receive transfers against the realization of short-term health shocks, such as illnesses.

From the Tobit model, the APEs of long-term health shocks, measured in terms of the number of physical disabilities, are significant for transfers sent from Group I (non-resident family members). However, the APEs become insignificant when social distance along blood-line and kinship increases to Group II, Group III, and Group IV. This implies that household heads with physical disabilities receive more transfers from their non-resident family members but informal risk sharing among 'non-altruistic' individuals do not respond to health shocks. The result highlights the importance of altruistic motive along bloodline, among extended family members, when shocks are long term and individuals are less likely to reciprocate in the future. The result also corroborates with findings from other studies in the literature, such as DeWeert and Fafchamps (2011), and Dercon and Krishnan (2000), which find informal risk sharing against health shocks along blood-line or kinship. The results from our estimation, however, should be interpreted with caution as they are sensitive to model selection. The APEs from the probit model are statistically insignificant.

The results also show that as the APEs on age for Group I and Group II are positive and statistically significant, implying that households receive more transfers from their close relatives. Moreover, it implies that age social network group, such as friends and neighbors who are not related along bloodline (Group III) and benevolent institutions (Group IV) do not consider age in their decisions to make transfers. Not surprisingly, the results implying that older members of the community who are less likely to reciprocate in the future, seems to be excluded from non-altruistic informal risk sharing arrangements but receive assistance from family and relatives. The result is consistent for different model specifications.

Table 3: Average partial effects of key variables on probability of making transfer: correlated random effects dynamic SUR Probit model

	No. of households = 1380, No. of observations = 4140											
	Group I			Group II			Group III			Group IV		
Variable	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Lagged dependent variable	**−0.012***	**−0.010***	**−0.011***	**−0.028***	**−0.028***	**−0.029***	−0.010	**−0.026***	**−0.026***	**−0.076***	**−0.076***	**−0.076***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.055)	(0.006)	(0.007)	(0.012)	(0.012)	(0.012)
Diff: No. of ill days	0.0003		0.0003	0.0000		0.0001	0.0001		0.0001	−0.0004		−0.0003
	(0.0002)		(0.0002)	(0.0004)		(0.0004)	(0.0003)		(0.0002)	(0.001)		(0.001)
Diff: No. of disabilities		0.0009	0.0007		0.001	−0.002		−0.001	−0.001		−0.004	−0.003
		(0.0007)	(0.0007)		(0.001)	(0.002)		(0.001)	(0.001)		(0.003)	(0.003)
Diff: Age	0.0004*	0.0003*	0.0002*	0.0003	0.0003*	0.0004*	−0.0001	−0.0001	−0.0001	0.0003	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0004)	(0.0003)
Var. of unobserved.	2.465*	1.513*	1.675*	0.714*	0.633*	0.743*	0.224*	0.217*	0.202*	0.059*	0.062*	0.059*
Heterogeneity ($var(\alpha_{ji})$)	(0.518)	(0.292)	(0.255)	(0.129)	(0.142)	(0.124)	(0.077)	(0.061)	(0.072)	(0.011)	(0.011)	(0.010)
Initial conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of households	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380
No. of observations	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140

Note: Covariates included in the model but not reported in the table include: log(non-food expenditure), sex of household head, household size, marital status, size of land owned, log of value of livestock, and education of the head. Time means include mean of the difference in log (non-food expenditure), household size, size of land owned (hectare) and log(value of livestock). For initial conditions, we include the log of transfers made in period 1. 'Diff: variable name' in column 1 indicates the covariate used is obtained as the difference between the value of the variable for the household and the village average.

Sender groups: I. Non-resident family members, II. Relatives, III. Friends, neighbors, members of Iqqub and *Iddir*, and IV. Church, mosque, NGOs, government organizations

* Indicates that the coefficient is statistically significant (the coefficient divided by the standard deviation is greater than or equal to two).

Table 4: Average partial effects from random effects dynamic SUR Tobit model

	Dependent variable: log of transfers; No. of households = 1380, No. of observations = 4140											
	Group I			Group II			Group III			Group IV		
Variable	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Lagged dependent variable	0.007	0.009	0.008	**−0.054***	**−0.064***	**−0.045***	**−0.109**	**−0.127***	**−0.149***	**−0.123***	**−0.116***	**−0.122***
	(0.010)	(0.011)	(0.012)	(0.019)	(0.028)	(0.022)	(0.058)	(0.056)	(0.077)	(0.025)	(0.026)	(0.030)
Diff: No. of ill days	0.002*		0.001	0.001		0.001	0.0001		0.0001	−0.005		−0.004
	(0.001)		(0.002)	(0.003)		(0.003)	(0.002)		(0.002)	(0.022)		(0.005)
Diff: No. of disabilities		**0.018***	**0.016***		−0.016	−0.016		−0.005	−0.005		−0.002	−0.004
		(0.007)	(0.007)		(0.014)	(0.014)		(0.011)	(0.010)		(0.022)	(0.023)
Diff: Age	0.002*	0.002*	0.002*	0.004*	0.005*	0.004*	−0.001	−0.001	0.001	0.002	0.002	0.0025
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Var. unobserved.	24.954*	24.354	19.155	42.945*	76.338*	50.550*	4.732*	4.904*	4.634*	1.776*	1.897*	1.821*
Heterogeneity ($var(\alpha_{ji})$)	(11.450)	(17.096)	(11.019)	(11.161)	(38.771)	(18.998)	(1.613)	(1.435)	(1.435)	(0.512)	(0.465)	(0.563)
Var. of idiosyncratic error	81.309*	118.822*	121.281*	90.25*	105.92*	88.21*	33.03*	40.6*	38.67*	36.38*	37.98*	33.63*
($var(\varepsilon jit)$)	(12.163)	(21.632)	(34.422)	(15.605)	(23.618)	(22.251)	(5.167)	(7.928)	(5.547)	(4.753)	(5.532)	(5.044)
Fraction of variance due to unobserved $\left[\frac{var(\alpha_{ji})}{var(\alpha_{ji})+var(\varepsilon_{jit})}\right]$	0.235	0.17	0.136	0.322	0.419	0.364	0.125	0.11	0.11	0.047	0.048	0.051
Initial conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Covariates included in the model but not reported in the table include: log(non-food expenditure), sex of household head, household size, marital status, size of land owned, log of value of livestock, and education of the head. Time means include mean of the difference in log(non-food expenditure), household size, size of land owned (hectare) and log(value of livestock). For initial conditions, we include the log of transfers made in period 1. 'Diff: variable name' in column 1 indicates the covariate used is obtained as the difference between the value of the variable for the household and the village average.

Sender groups: I. Non-resident family members, II. Relatives, III. Friends, neighbors, members of Iqqub and *Iddir*, and IV. Church, mosque, NGOs, government organizations

* Indicates that the coefficient is statistically significant (the coefficient divided by the standard deviation is greater than or equal to two).

5.2 History Dependence/Limited Commitment

Consistent with the theory, we find negative history dependence among non-altruistic risk sharing partners (Group III). All other factors held constant, households who received transfers in the current period from Group III are less likely to receive the same amount in the next period from the same group. For instance, the estimated APEs from the Probit model (see Table 3, Group III, column (iii)) imply that a household who received a transfer from sender Group III this period has a 2.6 per cent lower chance of receiving a transfer from the same group in the next period. Similarly, from the Tobit model (see Table 4, Group III, column (iii)), the estimated elasticity is -0.149, implying that if a transfer from a friend in the current period increases by 10 per cent, the amount that he/she transfers in the next period decreases by 1.5 per cent.

Interestingly, in both DSUR Probit and Tobit models, the APEs on the lagged dependent variable are negative and statistically significant for sender Group II and Group IV, suggesting history dependence even among altruistically motivated partners, such as relatives and formal and religious institutions. However, we find no evidence of history dependence for Group I, which is expected in the presence of strong altruism that makes the participation constraint irrelevant and, hence, no limited commitment (Fafchamps, 2011). The magnitude of the coefficient also suggests that the extent of limited commitment tends to dissipate as the degree of altruism increases (see results from the Tobit models in Table 4). Therefore, one can deduce that in rural Ethiopia limited commitment is evident among non-altruistic risk sharing partners but it tends to weaken as ties among partners become stronger particularly along bloodline.

5.3 Strategic Interaction among Networks

Another important question that our study attempts to answer is how networks interact. The estimated correlations among the four transfer equations corresponding to the different social network groups provide a good measure on the direction and magnitude of interaction among these groups. The estimated correlations are presented in Tables C.4 and C.5 of supplementary Appendix C for the static and dynamic versions of our models.

If we ignore the covariates for the purpose of illustration, a transfer from network j to household i can be written as the sum of the two components $\tau_{jit} = \alpha_{ji} + \varepsilon_{jit}$. The first component (α_{ji}) does not change over time and could be interpreted as entitlement or transfer made to the household regardless of current circumstances. Alternatively, one can interpret this component as planned or predetermined before the realization of shocks. Whereas the second component (ε_{jit}) represents the idiosyncratic component of transfer, which varies over time, such as emergency assistants. Our model captures the interactions along these two components of transfers, that is, $corr(\alpha_{mi}, \alpha_{nit})$ and $corr(\varepsilon_{mit}, \varepsilon_{nit})$. These correlation matrices not only unfold interesting interactions among social networks groups m and n but also the specific components of transfer. Negative values imply crowding out, whereas positive values imply complementarity among networks.

The results in Appendix C Table C.4 show that the magnitude of the correlations between the time-invariant components of transfers, $corr(\alpha_{mi}, \alpha_{nit})$, are larger than the magnitude of correlations along the idiosyncratic components $corr(\varepsilon_{mit}, \varepsilon_{nit})$. However, the correlations on the idiosyncratic components are statistically insignificant in all models. In the dynamic Tobit model (Table C.5, column (iii)), the correlation between the time-invariant component of transfers from Group I and Group II is 0.55, which is also statistically significant. This implies that these two networks, non-resident family members and relatives, significantly complement the amount of planned component of transfers. The results also show some complementarity between Group I and Group III but the correlations are statistically insignificant. With regard to interaction on the idiosyncratic component of transfers, the correlations are statistically and economically insignificant. This is true in all models and specifications. We can, therefore, deduce that social networks do not appear to strategically coordinate an idiosyncratic or unplanned component of transfers, which are more likely to be made in response to shocks or unexpected circumstances.

Finally, we assess the heterogeneity in risk sharing. One way to assess the degree of heterogeneity is by inspecting the distribution of unobserved individual heterogeneity. In the absence of heterogeneity, the estimated coefficients collapse to a point mass (degenerate) with zero variances. However, the estimated variances of the unobserved heterogeneity are different from zero and statistically significant in all models (see Tables C.2, C.3, 3 and 4). Figure 1 also shows that the distributions of the unobserved heterogeneity terms are non-degenerate.

5.4 Further Discussions

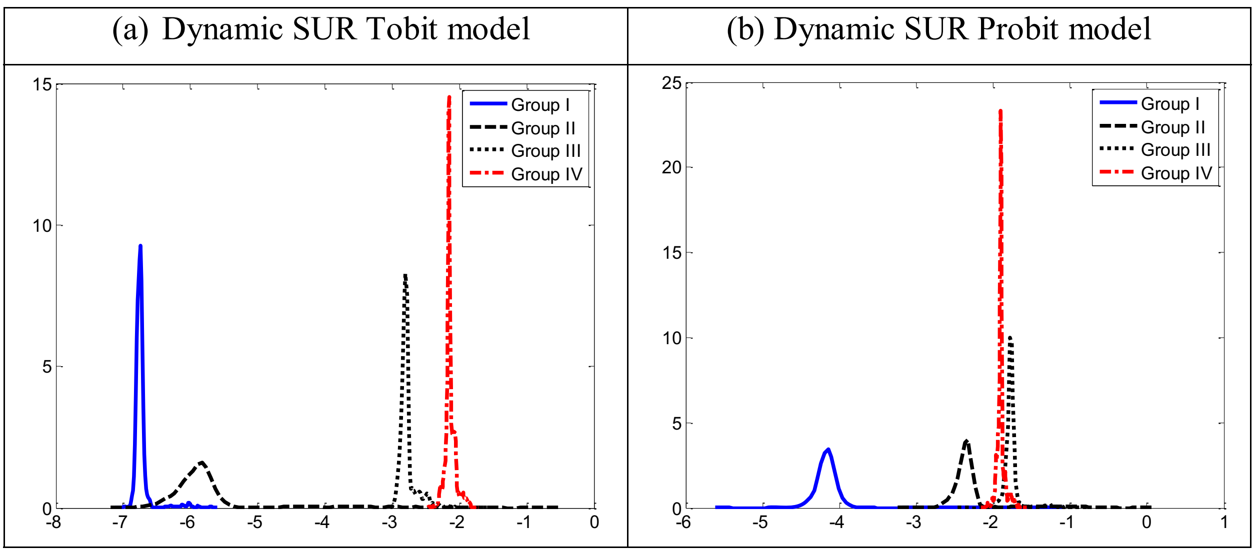
The results suggest that households in rural Ethiopia are susceptible to the consequence of health shocks. In light of our findings that households do not receive assistances either from non-altruistic informal risk sharing networks or formal institutions such as religious, government and non-government organizations, the detrimental impacts of unexpected health shocks and the risk of catastrophic out-of-pocket health care expenditure could be considerable (Akinkugbe and Chama-Chiliba, 2012). In the absence of formal health insurance and financing systems, the typical coping mechanisms against such shocks, as in many other low-income rural areas, are to sell productive assets such as oxen, borrow at a high interest rate, or completely forgo healthcare altogether just because they cannot afford it. These sub-optimal coping mechanisms entail considerable welfare loss and could push them into the poverty trap.

Although we find no significant interaction between other networks, what is intriguing is that, whatever strategic interaction therein, the magnitude is more pronounced on the planned component of transfers as opposed to the unplanned or idiosyncratic component pertinent to transitory/short-term health shocks. The implication is that, given complementarities of transfers, should an individual realize short-term illness, the amount and likelihood of receiving transfers from family members, who typically provide assistance regardless of future reciprocity, is low. In essence, when help is most needed due to unforeseen short-term illnesses, receiving it is difficult, even from close family members. This shows that, although households receive some sort of support from close family members, it is limited or non-existent against the more common short-term health shocks. Furthermore, not only do we find significant negative history dependence in transfers suggesting limited commitment among non-altruistic groups but also in transfers from close family members, relatives, and formal institutions, suggesting the tendency to discourage dependency as opposed to limited commitment *per se*.

To sum up, the findings highlight that rural households are largely exposed to the risks of healthcare shocks and assistance from informal risk sharing networks are rarely available to cushion households from the financial, health, and welfare impacts of health shocks. Introducing health insurance systems or other third-party healthcare financing mechanisms would increase welfare significantly (Mwabu et al., 2002). Recently, Ethiopia started to pilot innovative community-based (mutual) health insurance schemes in selected rural villages and these are expected to be gradually rolled out to all rural villages. Other countries such as Rwanda have reached coverage of up to 90 per cent of the population through community-based health insurance schemes.

Our study is not without caveats. The panel data cover periods between 1994 and 1997, which is over 20 years. The concern is that the findings might not reflect the current market, institutional, cultural settings in rural Ethiopia. However, much has not changed in terms of the country's health insurance landscape, where formal health insurance coverage is below 2 per cent,

Figure 1: Kernel Distribution of Unobserved Individual Heterogeneityfx1



underscoring that the results could still be valid. Furthermore, the results show how interrelated social network groups behave. Without rapid social, cultural, and religious changes that significantly alter the social network behavior, the results should still hold true.

6. Conclusion

Although it is evident that informal risk sharing networks provide some sort of insurance against income and consumption shocks, little is understood on whether the same holds true for health shocks, especially in the presence of multiple and interacting social networks. Using household panel data from rural Ethiopia, we provide empirical evidence on informal risk sharing against short-term and long-term health shocks. Using correlated random effects dynamic SUR Probit and Tobit models, we account for strategic interaction in social networks, which could complement or crowd each other out. In the model, we address various empirical issues and pin down the specific component of transfer that social networks strategically interact on.

We find no evidence of informal risk sharing against health shocks among non-altruistic individuals. However, transfers from networks related along bloodlines (non-resident family members and relatives) significantly respond to health shocks, particularly to long-term health shocks. These findings, undoubtedly, highlight the importance of altruism in the rural risk sharing network topology. Our study also finds that families strategically complement their planned component (such as regular remittances, entitlements, and chop money) of transfers. However, we find no statistically significant strategic interaction on either idiosyncratic or planned components of transfers between other social networks.

The take-home message is that health shocks remain to be important risks which are not well insured in rural Ethiopia. Although extended family members and relatives provide some assistance in response to health shocks, it is insufficient especially against transitory health shocks, such as illnesses, leaving households to absorb substantial part of the impacts. Formal interventions such as community-based health insurance schemes, therefore, could fill such a gap. In the absence of significant crowding out between formal institutions and informal risk sharing networks, such interventions could be welfare increasing.

Notes

1. See Anyanwu and Erhijakpor (2009) for the link between health expenditures and health outcomes in Africa.
2. The survey was conducted in collaboration with Economics Department, Addis Ababa University, and the Centre for the Study of African Economies, University of Oxford. The funding for the survey was provided by the Economic and Social Research Council, Swedish International Development Agency, United States Agency for International Development, and the World Bank. The data are publicly available at various online repositories and web links and a detailed description of the survey can be found at http://www.csae.ox.ac.uk/datasets/Ethiopia-ERHS/ERHS-main.html.
3. Supplementary appendices A through C are available at: http://www2.gsu.edu/~ecosgg/research/pdf/WG_ADR2017.pdf

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