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Andinet Woldemichael
African Development Bank

Shiferaw Gurmu
Georgia State University, sgurmu@gsu.edu

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Andinet Woldemichael
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Shiferaw Gurmu
Georgia State University

Andrew Young School
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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. 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.

Keywords: altruism, crowding out, poverty, social networks, health insurance

JEL Classification: D01; D10; D64; D85; I1.

* African Development Bank, Abidjan
† Corresponding author: Department of Economics, Andrew Young School of Policy Studies, Georgia State University, Atlanta, GA 30303. Email: sgurmu@gsu.edu

1. Introduction

Risks and shocks are fundamental to the creation and reproduction of poverty. Not only 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 through transfers responds to 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 crowding-out – among networks and if so to what extent it determines the ability of households to cope with shocks.

Like many other low-income countries, people in rural villages in Ethiopia have limited access to formal health insurance products against health shocks. Insurance markets broadly and health insurance in particular are largely missing and tax-based public insurance systems and social protection programs are non-accessible to the majority of people in rural areas. Until early 2000, formal health insurance was not available to the population in Ethiopia, and it is still underdeveloped. For instance, the percentage of people covered by health insurance in 2011/12 is only 1.13% in rural areas and 2.47% in urban areas of Ethiopia (FMoH 2014). The health insurance coverage across rural and urban areas of Ethiopia in 2007/08 was 0.32% (FMoH 2014). Consequently, health shocks are largely absorbed by the individual herself and/or support from informal social networks such as relatives, friends, and neighbors. The extent to which these networks provide cushion against the different forms of idiosyncratic health shocks – short-term or long-term – is not clear, especially in the presence of overlapping social networks. Gurmu and Tesfu (2011) provide details about health care system of Ethiopia.

Our study contributes to the literature by empirically investigating how informal risk sharing through transfers from different networks responds to health shocks. We conduct our analysis separately for short-term and long-term health shocks. Categorizing health shocks into short- and long-term allows us to separately assess risk sharing against transitory illnesses and persistent shocks such as disabilities, which have higher welfare effects (Fafchamps and Kebede, 2008).

The data are assembled from four rounds of panel data covering about 1,480 households in 15 rural villages in Ethiopia between 1994 and 1997. We consider transfers from different 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 to a household along bloodline, we classify all possible networks which made cash or in-kind transfers into four groups: i) non-resident family, ii) relatives, iii) friends, neighbors, fellow members of informal savings and credit associations, and iv) formal institutions such as church, mosque, government, and non-government organizations.

In terms of methodology, we implement econometric methods which take into account the richness of the survey data and the non-normal distribution of transfers. The dependent variable is transfer with large proportion of households receiving zero amounts which arises due to either a corner solution where individuals decide to make zeros transfers or transfers are not in the choice set. We address such non-linear distribution in transfers using probit and Tobit specifications in a dynamic random effects model addressing initial conditions problem. Specifically, we implement Dynamic Correlated Random Effects Seemingly Unrelated Regression (D-SUR) Probit and Tobit models. These models handle not only the aforementioned empirical issues but also the inherently dynamic risk sharing models in the presence of multiple and interdependent networks. Unlike single equation models, SUR model allows for transfers from one network to be correlated, providing important evidence on the extent and direction of interaction among networks.

What makes our model even more appealing is that it captures the interactions among networks not only on the time-varying idiosyncratic component but also on the time-invariant component 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 which are made on a regular basis such as remittances, entitlement, and chop money. Due to computational complexity involving D-SUR Probit and Tobit models as well as the lack of standard statistical software packages for these models, we use 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 long-term health shocks. The same network makes more transfers to households headed by senior members of the village, suggesting altruism/social norms in that transfers are made without anticipating future reciprocity. On the other hand, transfers from networks such as friends, neighbors, and fellow members of informal savings, credit, and funeral associations respond to neither short-term nor long-term health shocks. We also find significant history dependence in transfers from not only genetically distant networks but also extended family members as well as formal institutions. Finally, the results suggest significant heterogeneity in both the probability and the amount of transfers.

The remaining part of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses the data and descriptive statistics. 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, even in the absence of formal insurance institutions, Pareto optimum could be achieved through informal risk sharing contracts among self-interested risk-averse individuals (Coate and Ravallion, 1993; Kocherlakota, 1996; Fafchamps, 1999; Ligon et al., 2002). In agreement with the theory, empirical evidence, mainly from developing countries, support the existence of at least partial risk sharing against idiosyncratic income and consumption shocks at various levels (Townsend, 1994; Ravallion and Chaudhuri, 1997; Morduch, 1991, 2002; Deaton; 1995; Udry, 1990 and 1994; Grimard, 1997). However, when it comes to shocks such as illness, evidence of risk sharing among self-interested villagers are rather bleak. There is little or no evidence of risk sharing against health shocks among self-interested individuals. For instance, 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 the network and village levels (DeWeerdt and Dercon, 2006).

The story, however, changes when motives other than self-interest such as emotions enter the picture. The most important emotion in the context of risk sharing is altruism. The roles of altruism and other motives in enforcing informal contracts are comprehensively reviewed in Fafchamps (2008). Altruism is understood as strong emotional reward for helping others and can potentially serve as enforcement instrument for informal arrangements. Altruism along bloodline, clan, and religious affiliations are by far the most important motives for risk sharing (Fafchamps, 2008; DeWeert and Fafchamps, 2011; Fafchamps and Lund, 2003). For instance, 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 where altruistic motive along bloodline is expected to be strong. Such risk sharing behavior among altruistically motivated individuals is observed because for sufficiently large motives the voluntary participation constraint becomes irrelevant and individuals provide assistance to their partners without the anticipation of future reciprocity (Foster and Rosenzweig, 2001; Fafchamps, 2008).

Furthermore, motives arising from social norms and customs are well recognized in determining individuals' sharing decisions (Fafchamps, 2008; Ligon and Schechter, 2012; Fehr and Falk 2002, Fehr and Schmidt 1999; 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 evidence from laboratory and field experiments on the roles of social norms include Morsink (2014) using field experiment in Ethiopia, Barr and Stein (2008) using funeral attendance in Zamabia, and Mirsut (2008) using data from inter-household transfers in Romania. For instance, Morsink (2014) find that more than 92% of non-altruistic farmers in rural Ethiopia make transfers based not only on self-interest but also on a combination of social preferences including inequality aversion and avoidance of punishment due to deviations from the sharing norm of the village.

Risk sharing motives and a host of other factors including imperfect and asymmetric information give rise to heterogeneity in risk sharing behavior and determine the way networks are endogenously formed, the extent and efficiency of risk sharing, and the distribution of welfare (De Weerdt and Dercon, 2006).

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 studying risk sharing in overlapping networks and endogenous network formation, such as Genicot and Ray (2003) and Fafchamps and Gubert (2007), little is understood about the implications of strategic interactions between these networks on welfare and risk sharing against idiosyncratic shocks such as illness and disability. Furthermore, most of the previous studies implicitly presume networks are exclusive ignoring possible strategic interactions and heterogeneity in risk sharing motives. This paper addresses these issues in the context of household survey panel data from rural Ethiopia.

Our focus on health shocks and informal risk sharing networks is also of wider importance to formal risk sharing arrangements and the interaction between them. There is substantial interest on how formal insurance institutions such as index-based crop insurance and community-based health insurance programs interact with informal risk sharing networks and vice-versa (Dubois et al., 2008). In countries such as India and Ethiopia, for instance, farmers are offered index-based crop insurance in villages where there already exists elaborate informal risk sharing networks. There is evidence in the literature that the interaction between social networks groups is important. For instance, 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 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. On the contrary, a study in Vietnam finds that informal risk sharing arrangements crowd out formal insurance markets (Wainwright and Newman, 2011). These findings highlight the importance of strategic interaction between formal and informal institutions. However, the implications of such strategic interactions among social networks in providing insurance against idiosyncratic health shocks is not well understood. This study fills the gap by modeling informal risk sharing against health shocks in the presence of multiple social networks.

3. Data and Descriptive Statistics

The study uses longitudinal data from the Ethiopian Rural Household Survey (ERHS)[1] which is one of the longest running household panel surveys in Africa. Started in 1989, the original survey includes seven villages. Since 1994, it was expanded to cover 15 peasant associations (PAs) in four regions with a sample size of approximately 1,480 households. In this paper, we use the first four rounds collected in the 1990s, i.e., the 1994a, 1994b, 1995, and 1997 rounds which provide a balanced panel with minimal attrition rate of around 6.7%. The dataset includes detailed information on households' demographic characteristics, consumption, health conditions, shocks, incomes, farming activities, informal networks, and transfers.

The dependent variable is logarithm of 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 the size of total land, the value of livestock owned and the logarithm of non-food expenditure as proxies. Besides, we include education to control for investment in health, health behavior, and household's performance in the local labor market. Other set of control variables include demographic characteristics such as household size, marital status, and sex.

Table 1 presents descriptive and summary statistics of the variables. Tables 2 and 3 present detailed summary and description of transfers. The data show that average household head in rural villages is unable to work for eight days in a year due to illnesses. Conditional on being ill and unable to work, he/she losses about 36 work days in a year. The number of days ill is right censored at 30 days. Censored observations account for 12.65% of households who reported to be ill and unable to work. Hence, averages are biased downwards. When it comes to disability, about 26% of household heads reported to have at least one physical disability. Out of the five indicators, the average number of disabilities a household head has is 0.7.

<< Table 1 about here >>

As shown in Table 2, about 20% of households in rural Ethiopia received transfers from different sources. 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% 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% 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.

<< Table 2 about here >>

The pooled data also show that about 22% of households received transfers from non-resident family members and relatives underscoring the importance of sharing along bloodline and kinship. As shown in Table 3, 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 3 about here >>

4. Econometric Strategy

The empirical models are based on the theory of informal risk sharing strategies with limited commitment where individuals voluntarily participate in sharing arrangement in anticipation of future reciprocity. Such an arrangement results in Pareto-optimal allocation even among non-altruistic self-interested individuals (see, for instance, Thomas and Worrall, 1988; Kocherlakota, 1996). The introduction of altruism in the model, however, relaxes the participation constraint and assistances could be provided without the anticipation of future reciprocity given that such motive is strong (De Weerdt and Fafchamps 2011; Fafchamps, 2008). 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 B on the author's website.

4.1. Benchmark Model

In the data, transfers are reported at a household level and information on the characteristics of the sender/s is limited. Using their response on the relationship of the sender for a particular transfer, we categorize transfers originating from four network groups denoted by j and estimate a recipient-level regression in a SUR framework allowing interaction among 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 group j to household i can be written as

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

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 age of the head for household i and the village average capturing biological survival rate. Further, $\boldsymbol{x}_{it}$ is a vector of other control variables, ε_{it} is the error term which is assumed *i.i.d.*, γ and $\boldsymbol{\beta}$s are coefficients to be estimated, and α_i is household specific intercept capturing unobserved individual heterogeneity. In the presence of limited commitment, γ is expected to be negative. Following literature, we include some of the variables in deviations from village averages. One of the key variables is the difference between income of individual i from j. Since village can be considered as partner j, these variables are included as deviations from the village averages.

Estimating the dynamic unobserved effects model presented in Equation (1) poses a number of challenges including initial conditions problem, interdependence of transfers among different groups, and censoring in transfer amount due to corner solutions. In the frequentist framework, Fixed Effects (FE) is a common approach to deal with unobserved individual heterogeneity without imposing restricted distributional assumptions. However, when the model becomes dynamic, FE estimate is usually biased and inconsistent in short panel like ours (*e.g.*, Nickell, 1981). The presence of heavy censoring in transfers also makes FE approach complicated. In such cases, dynamic correlated random effects (RE) model is appealing which also makes estimating non-linear models such as Probit and Tobit models easier.

In order to control for the correlation between the unobserved individual effects and the covariates, we follow Woodridge's (2005) approach and include time-means of selected time-varying independent variables and first round transfer amount in the model; see also Mundlak

(1978) and Chamberlain (1980). Such an approach minimizes the initial conditions problem and provides consistent estimates when the unobserved individual heterogeneity and some of the time-varying covariates are correlated.

Censoring due to corner solutions is another important issue in our case which arises due to substantial “pile-up” of transfers at zero. In the data, 80% of the pooled sample reported receiving zero transfer and when disaggregated by group, the percentage increases to more than 90%. Left unaddressed, censoring could result in exaggerated slope estimates, commonly referred to as “expansion bias”, mainly on the lagged value (Rigobon and Stoker, 2007). Our dynamic model specification also address 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 (lagged values), potential feedback effects/endogeneity are less of an issue.

4.2. The Model with Strategic Interaction between Social Networks

The proposed benchmark model, which parsimoniously addresses the empirical issues discussed above, is single-equation model that do not allow for strategic interaction of transfers from different social networks. We now present empirical model that addresses all empirical issues discussed above as well as strategic interaction among social networks in a DSUR setup. Although Li and Zheng (2008) propose dynamic Tobit model using Semiparametric Bayesian approach in a single equation problem, estimating DSUR Tobit model using standard statistical software packages is difficult due to lack of readily available econometric routines. Hence, we estimate the DSUR model described below in a hierarchical Bayesian estimation framework (details are given in a supplementary appendix available from the authors).

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 dynamic SUR Tobit model can be written as follows

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

$$\tau_{mit} = max(\tau_{mit}^*, 0),$$

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, following Wooldridge (2005) 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:

$$\alpha_{mi} = \delta\tau_{mi0} + \boldsymbol{X}_{mi}b^m + u_{mi}, \qquad (3)$$

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

$$\boldsymbol{u}_i = [u_{1i}, u_{2i}, u_{3i}, u_{4i}] | \tau_{i0}, \boldsymbol{X}_i \sim N(\boldsymbol{u}, \boldsymbol{\Sigma}), \qquad (5)$$

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, i.e. off-diagonal elements of Ω and Σ, respectively, and are $M \times M$.

In order to estimate the random effects DSUR Tobit model given by equations (2)-(5), we use an efficient Bayesian estimation method with data augmentation technique (Albert and Chib 1993). This approach treats the latent variables and the unobserved individual heterogeneity terms as additional parameters to be explicitly estimated using MCMC simulations techniques. The likelihood function, the joint posteriors of all parameters, the estimation algorithm, and the mathematical expressions for the average partial effects (APEs) for correlated RE DSUR Tobit model are given in a supplementary appendix. We also estimate RE DSUR Probit model as an alternative by dichotomizing receipt of transfers into binary indicators to model probability of positive transfers. However, given the similarity with the above modeling strategy adopted for Tobit framework, we do not present the likelihood function and the estimation algorithms of the model based on binary probit to save space.

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. Tables 4 and 5 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 short-term and long-term health shocks are included in the model. The results from the dynamic version of the models are given in tables 6 and 7, with the underlying coefficient estimates for the dynamic Tobit given in Table A.1 of Appendix A.

5.1 Health Shocks and Risk Sharing

The results from the static and the DSUR 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 7, 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 assistance from others against the realization of short-term health shocks such as transitory illnesses.

The results on long-term health shocks, measured in terms of the number of physical disabilities of the head, are rather sensitive to the econometric models. The APEs from the Tobit models are significant for transfers sent from Group I (non-resident family members). This implies that household heads with a number of physical disabilities receive more transfers from their non-resident family members. As shown in the tables, however, the APEs become insignificant when social distance along blood-line and kinship increases to Group II, Group III, and Group IV. This evidence suggests that informal risk sharing among "non-altruistic" individuals do not respond to health shocks and highlights that if long-term health shocks are insured through informal risk sharing networks, it is mainly due to risk sharing among extended family members. This result also corroborates with findings from other studies in the literature such as DeWeert and Fafchamps (2011), and Dercon and Krishnan (2000) which find that existence of informal risk sharing in times of illness mainly from individuals related along bloodline or kinship. However, the results should be interpreted with caution as they are sensitive to model selection.

The APEs on long-term health shocks from the probit models are all statistically insignificant highlighting that regardless of social distance, transfers are not responsive to long-term health shocks.

<< Table 4 about here >>

<< Table 5 about here >>

<< Table 6 about here >>

<< Table 7 about here >>

The findings further show that as the difference between the age of household head and the village average increases, households receive more transfers from their socially close relatives (groups I and II). This is consistent across all model specifications, except in the static Probit model for Group II. However, age of household heads does not have significant impact on transfer decisions of sender Group III such as friends and neighbors who are not related along bloodline. The same holds true for Sender Group IV (benevolent institutions such as churches, mosques, and NGOs) in that age of the recipient does not have significant effect on the decision and amount of transfers. This remains true regardless of model specification. With regards to helping older members of society who are less likely to reciprocate in the future, the results highlight that altruistic and social norms are the most important motives.

5.2 History Dependence/Limited Commitment

Theory suggests that limited commitment is a prominent feature of informal risk sharing arrangement among non-altruistic risk averse agents. The common empirical approach to test and account for limited commitment (history dependence) is to estimate dynamic models. In agreement with the theoretical prediction, we find negative history dependence among non-altruistic risk sharing partners (Group III). The implication is that, all other factors held constant, households who received transfers in the current period from Group III are less likely to receive the same amount of transfer in the next period from the same group. For example, the results from the Probit model (see Table 6, Group III, column (iii)) imply that a household who received aid from sender Group III this period has a 2.6% lower chance of receiving transfer in the next period in an event that they face identical health shocks. Similarly, from the Tobit model (see Table 7, Group III, column (iii)), the estimated elasticity is -0.149 implying that if transfer received from a friend in the current period increases by 10%, the next period amount from the same network decreases by 1.5%.

Interestingly, in both DSUR Probit and Tobit models, the APEs of the lagged dependent variable are negative and statistically significant even for sender Group II and Group IV. This suggests some evidence of history dependence among altruistically motivated partners such as relatives and formal and religious institutions. However, the evidence on limited commitment is inconclusive or absent for Group I who constitutes genetically close partners (non-resident family members) and are presumed to have stronger altruistic motives. Although the coefficient is negative and statistically significant in the probit model, it becomes positive and insignificant in the dynamic Tobit model which suggests that there is no conclusive evidence that the participation constraint binds for these socially close partners. This result is expected in the presence of strong altruism and social norms which makes the participation constraint or limited commitment becomes irrelevant (Fafchamps, 2008). The magnitude of the coefficients also suggest that the extent of limited commitment tends to dissipate as the degree of altruism, measured by genetic proximity, increases (see results from the Tobit models in Table 7). Hence, 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

The other important question that our study attempts to answer is how networks interact and, in particularly, how one group's decision to make transfers depends on the decisions of another social network groups. 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 (8) and (9) for the static and dynamic versions of our models.

If we ignore covariates for just the purpose of illustration, transfer from sender network j to household i can be written as the sum of the two components $\tau_{jit} = \alpha_{ji} + \varepsilon_{jit}$. The first component ($\alpha_{ji}$) 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 pre-determined before the realization of shocks. The second component (ε_{jit}) represents idiosyncratic part of transfer which changes over time such transfers made in response to shocks or emergencies. Our model captures the interaction between networks along these two separate components of transfers, i.e. $corr(\alpha_{mi}, \alpha_{nit})$ and $corr(\varepsilon_{mit}, \varepsilon_{nit})$. These correlation matrices not only unfold interesting interactions among social networks groups m

and n but also their interaction on the specific components of transfer. While negative values imply crowding-out, positive values imply complementarity among networks.

The results in Table (8) 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 9, 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, which are closely related to the household along blood-line 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.

<< Table 8 about here >>

<< Table 9 about here >>

With regard to interaction of networks on the idiosyncratic or time-varying component of transfers, the correlations are statistically and economically insignificant. This is true in all models and specifications. We can deduce that social networks do not appear to strategically coordinate 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 in the presence of multiple and interacting networks. One way to assess the degree of heterogeneity is by inspecting the distribution of unobserved individual heterogeneity. One of the advantages of Bayesian method with MCMC simulation techniques is that we can directly estimate those parameters the same way we estimate other model parameters. 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 4-7). Figure (1) also shows that the distributions of the unobserved heterogeneity terms are non-degenerate.

<< Figure 1 about here >>

5.4. Further Discussions

The results highlight that transfers from non-altruistic informal risk sharing networks such as friends, neighbors, and fellow members of informal savings, credit, and funeral associations respond to neither short-term nor long-term health shocks. However, there is some evidence that close family members and relatives, who are more likely to be altruistic along bloodline, make transfers in response to health shocks, particularly long-term health shocks. The same network makes more transfers to households headed by senior members of the village. The results suggest that altruism/social norms, without anticipating future reciprocity, play significant in providing assistance in times of illness, disabilities, and old age.

In the absence of formal health insurance and financing systems, therefore, 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. 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 all together just because they cannot afford. These sub-optimal coping mechanisms themselves entail considerable welfare loss and could push them into poverty trap.

With regards to strategic interactions among networks, networks which have close blood ties with the household such as nonresident family members and relatives complement each other's planned component of transfers. 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 which is, particularly, 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 very limited or does not exist against short-term health shocks, which are common in rural places. Furthermore, we find significant negative history dependence in transfers suggesting limited commitment among non-altruistic groups. Interestingly, there is also negative history dependence 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-part healthcare financing mechanisms would increase welfare significantly. Recently, Ethiopia started to pilot innovative community based (mutual) health insurance schemes in selected rural villages and expected to be gradually rolled out to the majority of rural villages. Other countries such as Rwanda have reached coverage of up to 90% of the population through community based health insurance schemes. Evidence show significant positive impacts on healthcare utilization rates and protecting households from health-related financial ruins (Woldemichael and Shimeles, 2015; Woldemichael et al. 2016; Lu et al., 2012; Shimeles, 2010).

Our study is not without caveats. The panel dataset covers 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, given that much has not changed in terms of the country's health insurance landscape, where formal health insurance coverage is below 2%, the results could still be valid. Furthermore, the results show how interrelated social network groups behave in response to realized health shocks. Unless there has been rapid social, cultural, and religious changes that significantly alter the social network behavior, the results should still hold true. Nonetheless, results should be interpreted with these caveats in mind.

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 possibly interacting networks. Using household panel data from rural Ethiopia, we provide empirical evidence on whether informal risk sharing arrangements provide insurance against short-term and long-term health shocks. We acknowledge and explicitly address multiple and possibly strategically interacting networks, which could complement or crowd each other out, using correlated random effects dynamic SUR Probit and Tobit models. In the model we address various empirical challenges and capture the extent of strategic interaction. Furthermore, the empirical model allows us to pin down the specific component of transfer that social networks interact.

We find no evidence of informal risk sharing against health shocks among non-altruistic individuals in rural Ethiopia. However, transfers from networks related along blood-line (non-resident family members and relatives) significantly respond to health shocks, particularly to long-term disabilities and senior members of society. These findings undoubtedly highlight the importance of altruism and social norms in the rural risk sharing network topology. Our study also finds that families and relatives constitute network groups which strategically complement the planned component (such as regular remittances, entitlements, and chop money) of transfer. However, we find no statistically significant strategic interaction on either idiosyncratic or planned components of transfers for other social networks constituting friends, neighbors, members of informal associations as well as formal institutions.

The take home message is that health shock remains to be important risk which is not well insured in rural Ethiopia where households absorb substantial part of the impacts. 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. Formal interventions such as community-based health insurance schemes could fill such gap in rural Ethiopia. In the absence of significant crowding-out between formal institutions and informal risk sharing networks, such interventions could be welfare enhancing.

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Appendix A: Additional Tables

Table A.1: Posterior Estimates of Coefficients of Correlated Random Effects Dynamic SUR Tobit Model
Dependent Variable: Log of Transfers; No. of households = 1380, No. of Observations = 4140

	Sender Group I		Sender Group II		Sender Group III		Sender Group IV	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Intercept	-32.86*	(3.80)	-21.74*	(3.09)	-9.57*	(1.60)	-10.23*	(1.36)
Lagged dep var 1	**0.85**	**(0.84)**	0.56	(0.70)	0.65	(0.66)	-0.53	(0.45)
Lagged dep var 2	1.70*	(0.67)	**-1.07**	**(0.60)**	-0.40	(0.70)	-0.27	(0.28)
Lagged dep var 3	-88.15*	(10.90)	0.83	(0.96)	**-6.13***	**(3.06)**	0.19	(0.33)
Lagged dep var 4	0.87	(0.59)	0.71	(0.37)	0.14	(0.25)	**-0.73***	**(0.14)**

D# ill days	0.10	(0.11)	-0.02	(0.10)	-0.01	(0.07)	-0.03	(0.04)
D# disabilities	1.24*	(0.49)	-0.46	(0.40)	-0.26	(0.35)	-0.01	(0.16)
Dage	0.14*	(0.05)	0.12*	(0.04)	-0.03	(0.03)	0.02	(0.02)
Dln non-food cons	0.85	(1.07)	0.54	(0.76)	0.64	(0.48)	-0.29	(0.26)
HH size	2.81*	(0.90)	0.87	(0.52)	-1.53*	(0.40)	-0.30	(0.21)
Land	-2.63*	(1.28)	0.15	(0.50)	0.73	(0.45)	-0.10	(0.20)
Ln livestock value	0.37	(0.49)	0.37	(0.35)	0.26	(0.27)	-0.02	(0.12)
Mln livestock value	-1.06	(0.55)	-0.70	(0.45)	-0.70	(0.35)	-0.08	(0.15)
Mhh size	-2.79*	(0.96)	-1.06	(0.57)	1.38*	(0.42)	0.47*	(0.22)
Mdln non-food cons	-0.81	(1.39)	1.14	(1.04)	-1.93*	(0.78)	-0.22	(0.39)
Initial lntransfer4	1.19	(1.01)	0.72	(0.54)	1.09	(0.84)	0.61*	(0.25)
Sex	-1.58	(2.96)	-6.74*	(2.01)	-0.12	(1.80)	0.44	(0.83)
Married	2.82	(3.04)	0.99	(1.99)	0.66	(1.86)	-0.43	(0.85)
Primary	-2.40	(1.55)	-1.65	(1.15)	-2.79*	(0.99)	-0.11	(0.53)
Junior	-9.92	(10.43)	-5.95	(4.21)	-3.82	(2.36)	0.36	(1.42)
Above high school	-18.35	(13.36)	1.77	(2.72)	-5.82	(2.99)	2.22	(1.49)
vDummies2	0.89	(6.29)	-38.33*	(18.63)	-15.88	(11.80)	10.05*	(1.27)
vDummies3	3.91	(5.34)	-7.24	(5.67)	-2.80	(4.72)	6.35*	(1.25)
vDummies4	5.60	(6.16)	-0.11	(3.93)	-15.27	(11.55)	-16.23*	(8.36)
vDummies5	6.68	(4.85)	-5.74	(3.69)	9.17*	(2.31)	12.70*	(1.26)
vDummies6	12.16*	(5.41)	-3.55	(3.61)	-7.09	(7.47)	-5.72*	(2.22)
vDummies7	13.11*	(6.23)	4.48	(3.89)	10.22*	(3.21)	7.26*	(1.52)
vDummies8	13.26*	(4.93)	8.34	(3.05)	5.28*	(2.71)	8.70*	(1.35)
vDummies9	13.70*	(4.67)	8.20	(3.19)	6.42*	(2.62)	-6.75*	(2.60)
vDummies10	16.71*	(4.88)	11.82	(3.11)	3.87	(3.76)	3.54*	(1.41)
vDummies11	11.78*	(5.40)	5.88	(3.22)	4.44	(3.43)	-2.32	(1.76)
vDummies12	0.81	(5.81)	-0.57	(3.31)	1.09	(2.69)	-5.47*	(2.01)
vDummies13	-8.00	(22.59)	-2.91	(4.57)	12.83*	(2.44)	0.17	(1.41)
vDummies14	-40.53	(23.29)	-144.03*	(24.43)	2.05	(3.06)	6.05*	(1.27)
vDummies15	16.05*	(4.68)	1.08	(3.32)	-10.64	(6.22)	-3.72*	(1.86)

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).

Time-means of covariates are shown by prefix M (e.g., Mhh size is the time-mean of household size, Hh size). VDummies indicate village dummy variables.

Other pertinent estimation results from the correlated random effects dynamic Tobit SUR model are shown in tables 7 and 9. In particular, the average partial effects based on the coefficient estimates reported in Table C.1 are given in Table 7.

Table 1. Variables Description and Summary Statistics

Description	Mean	Std. Dev.	Min	Max
Transfers:				
Log of all Transfers	0.878	1.793	0	7.638
Log of transfers excluding Religious/NGOs/Govt/Other	0.306	1.091	0	6.621
Log of transfers from Non-resident Family Members	0.054	0.497	0	5.956
Log of transfers from Other Relatives	0.167	0.842	0	6.621
Log of transfers from Friends/Neighbor/Iqqub/Iddir	0.094	0.564	0	5.303
Log of transfers from Religious/NGOs/Govt/Other	0.601	1.559	0	7.638
Disabilities and Illnesses:				
No. of Household Heads Disability (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 (>=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 disability is the sum of the following conditions: 1) difficulty to standup 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.

Table 2. Proportion of Transfer Recipients and Conditional Transfers by Rounds

Transfer type/Round	Proportions		Conditional Log Transfers		
	No. of Obs.	Mean	No. of Obs.	Mean	St. Dev.
Transfer from Any Sender	**5,803**	**20.66%**	**1,199**	**4.248**	**0.032**
Round 1	1,475	8.41%	124	3.969	0.09
Round 2	1,464	34.08%	499	4.738	0.05
Round 3	1,460	14.32%	209	4.037	0.066
Round 4	1,404	26.14%	367	3.797	0.05
Transfer from Sender Group I	**5,803**	**1.24%**	**72**	**4.379**	**0.981**
Round 1	1,475	0.88%	13	4.364	0.258
Round 2	1,464	1.43%	21	4.572	0.162
Round 3	1,460	1.03%	15	4.254	0.218
Round 4	1,404	1.64%	23	4.292	0.266
Transfer from Sender Group II	**5,803**	**4.10%**	**238**	**4.072**	**1.181**
Round 1	1,475	4.54%	67	3.966	0.128
Round 2	1,464	3.28%	48	4.215	0.17
Round 3	1,460	4.25%	62	4.275	0.148
Round 4	1,404	4.34%	61	3.869	0.168
Transfer from Sender Group III	**5,803**	**2.77%**	**161**	**3.376**	**0.633**
Round 1	1,475	0.81%	12	3.463	0.163
Round 2	1,464	2.05%	30	3.308	0.126
Round 3	1,460	1.44%	21	3.651	0.214
Round 4	1,404	6.98%	98	3.327	0.052
Transfer from Sender Group IV	**5,803**	**13.75%**	**798**	**4.369**	**1.103**
Round 1	1,475	2.58%	38	3.874	0.153
Round 2	1,464	29.51%	432	4.811	0.052
Round 3	1,460	8.42%	123	3.874	0.069
Round 4	1,404	14.60%	205	3.828	0.064

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

Table 3. Amount of Annual Conditional Transfers Received (in *Birr*) (1994 – 1997)

Sender type	No. of Obs.	Mean	Std. Dev.	Min	Max
Any Sender	**1,199**	**477.5**	**714.8**	**0.0**	**8,300.7**
Sender Group I	72	341.0	253.5	24.0	1,155.0
Sender Group II	238	323.8	405.8	1.9	2,250.0
Sender Group III	161	140.8	117.7	12.0	800.0
Sender Group IV	798	561.6	816.2	0.0	8,300.7

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.

Table 4. Average Partial Effects of Key Variables on Probability of Making Transfer
Correlated Random Effects SUR Probit Model
No. of households = 1380 =, No. of Observations = 5520

Variable	Group I			Group II			Group III			Group IV		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Diff: No. of ill days	0.0002		0.0002	0.000		0.0000	0.0001		0.0001	-0.0005		-0.0005
	(0.0002)		(0.0002)	(0.0004)		(0.0003)	(0.0003)		(0.0003)	(0.001)		(0.001)
Diff: No. of disabilities		0.001	0.001		-0.001	-0.001		-0.001	-0.001		(0.003)	-0.0023
		(0.001)	(0.001)		(0.001)	(0.002)		(0.001)	(0.001)		(0.003)	(0.003)
Diff: Age	0.0003*	0.0003*	0.0003*	0.0003	0.0003	0.0003	-0.0001	-0.0001	-0.0001	0.0003	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0001)	-0.0002	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)
Var. Unobse. Heterog.	1.422*	1.224*	1.617*	0.443*	0.417*	0.383*	0.146*	0.167*	0.157*	0.052*	0.051*	0.050*
	(0.401)	(0.320)	(0.361)	(0.103)	(0.100)	(0.095)	(0.053)	(0.052)	(0.045)	(0.011)	(0.010)	(0.009)
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	5,520	5,520	5,520	5,520	5,520	5,520	5,520	5,520	5,520	5,520	5,520	5,520

Note: Covariates included in the model but not reported in the table include: Log (nonfood 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). "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 5. Average Partial Effects from Correlated Random Effects SUR Tobit Model
Dependent Variable: Log of Transfers; No. of households = 1380 =, No. of Observations = 5520

Variable	Group I			Group II			Group III			Group IV		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Diff: No. of ill days	0.001		0.001	0.0001		0.001	0.0001		0.001	-0.003		-0.003
	(0.001)		(0.001)	(0.002)		(0.002)	(0.001)		(0.001)	(0.004)		(0.004)
Diff: No. of disabilities		**0.009***	**0.009***		-0.009	-0.010		-0.002	-0.004		-0.009	-0.007
		(0.004)	(0.004)		(0.008)	(0.008)		(0.006)	(0.007)		0.018	(0.018)
Diff: Age	0.002*	0.001	0.001	0.002*	0.002*	0.002*	-0.001	-0.001	-0.001	0.002	0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Var. unobserved. Heterogeneity ($var(\alpha_{ji})$)	7.976	16.967	4.552	4.099	4.472*	3.993*	2.694*	2.824*	2.911*	0.882*	0.935*	0.905*
	(5.769)	(11.844)	(2.489)	(2.058)	(1.633)	(1.117)	(1.013)	(1.013)	(1.355)	(0.213)	(0.220)	(0.249)
Var. of idiosyncratic error ($var(\varepsilon_{jit})$)	69.114*	73.17*	65.60*	47.86*	50.304*	51.826*	40.94*	40.015*	46.436*	29.301*	29.948*	29.968*
	(14.195)	(14.59)	(7.69)	(5.402)	(4.312)	(6.645)	(10.624)	(4.996)	(7.848)	(2.207)	(2.324)	(2.596)
Fraction of variance due to unobserved $\left[\frac{var(\alpha_{ji})}{var(\alpha_{ji})+var(\varepsilon_{jit})}\right]$	0.103	0.188	0.065	0.079	0.082	0.072	0.062	0.066	0.059	0.029	0.030	0.029
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 (nonfood 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). "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 6. 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

Variable	Group I			Group II			Group III			Group IV		
	(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. Heterogeneity ($var(\alpha_{ji})$)	2.465*	1.513*	1.675*	0.714*	0.633*	0.743*	0.224*	0.217*	0.202*	0.059*	0.062*	0.059*
	(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 (nonfood 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 7. Average Partial Effects from Random Effects Dynamic SUR Tobit Model

Dependent Variable: Log of Transfers; No. of households = 1380, No. of Observations = 4140

Variable	Group I			Group II			Group III			Group IV		
	(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. Heterogeneity ($var(\alpha_{ji})$)	24.954*	24.354	19.155	42.945*	76.338*	50.550*	4.732*	4.904*	4.634*	1.776*	1.897*	1.821*
	(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 ($var(\varepsilon jit)$)	81.309*	118.822*	121.281*	90.25*	105.92*	88.21*	33.03*	40.6*	38.67*	36.38*	37.98*	33.63*
	(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 (nonfood 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 8. Posterior Estimates of Correlation Terms among Time-invariant and Idiosyncratic Components of Sender Groups (Random Effects Static and Dynamic SUR Probit Models)

Sender Groups	Time-invariant component						Idiosyncratic component					
	Static Model			Dynamic Model			Static Model			Dynamic Model		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Group I and Group II	0.270	0.320	0.300	0.080	0.090	0.090	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.170)	(0.200)	(0.180)	(0.130)	(0.150)	(0.210)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Group I and Group III	0.100	0.130	0.180	0.010	-0.080	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.250)	(0.220)	(0.260)	(0.260)	(0.320)	(0.260)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Group I and Group IV	0.040	0.060	0.050	0.020	0.050	0.030	-0.010	-0.010	-0.010	-0.010	-0.010	-0.020
	(0.160)	(0.160)	(0.160)	(0.170)	(0.190)	(0.210)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Group II and Group III	0.190	0.070	0.220	0.070	0.070	0.160	-0.010	0.000	0.000	0.000	0.000	0.000
	(0.210)	(0.250)	(0.190)	(0.270)	(0.290)	(0.190)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Group II and Group IV	-0.020	-0.030	-0.080	-0.170	-0.120	-0.100	0.000	0.010	0.010	0.010	0.010	0.000
	(0.160)	(0.170)	(0.150)	(0.170)	(0.180)	(0.180)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Group III and Group IV	-0.020	-0.020	-0.070	-0.110	-0.120	-0.120	0.000	0.000	0.010	0.000	0.000	-0.010
	(0.160)	(0.170)	(0.160)	(0.170)	(0.170)	(0.170)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)

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

The main results and the underlying specifications are given in tables 4 and 6 above for static and dynamic versions, respectively.

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

Table 9. Posterior Estimates of Correlation Terms among Time-invariant and Idiosyncratic Components of Sender Groups (Random Effects Static and Dynamic SUR Tobit Models of Log Transfer)

Seder Groups	Time-invariant component						Idiosyncratic component					
	Static			Dynamic			Static			Dynamic		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Group I and Group II	0.180	0.330	0.070	**0.67***	0.490	**0.55***	0.000	0.000	0.000	0.000	0.000	0.000
	(0.340)	(0.340)	(0.250)	(0.210)	(0.260)	(0.210)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Group I and Group III	0.020	0.080	0.110	0.210	0.190	0.140	0.000	0.000	0.000	0.000	0.000	0.000
	(0.320)	(0.310)	(0.300)	(0.230)	(0.300)	(0.360)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Group I and Group IV	0.070	0.000	0.030	0.010	-0.050	-0.060	0.000	0.000	0.000	0.000	0.000	0.000
	(0.160)	(0.190)	(0.170)	(0.160)	(0.170)	(0.200)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Group II and Group III	0.050	0.090	0.030	0.220	0.280	0.090	0.000	0.000	0.000	0.000	0.000	0.000
	(0.200)	(0.270)	(0.340)	(0.230)	(0.230)	(0.310)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Group II and Group IV	0.060	0.030	-0.010	0.030	-0.010	0.000	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.170)	(0.170)	(0.190)	(0.180)	(0.190)	(0.180)	(0.020)	(0.020)	(0.020)	(0.020)	(0.030)	(0.030)
Group III and Group IV	0.040	0.000	0.000	0.010	-0.050	-0.020	0.000	0.000	0.000	0.000	0.000	0.000
	(0.170)	(0.200)	(0.180)	(0.190)	(0.220)	(0.200)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)

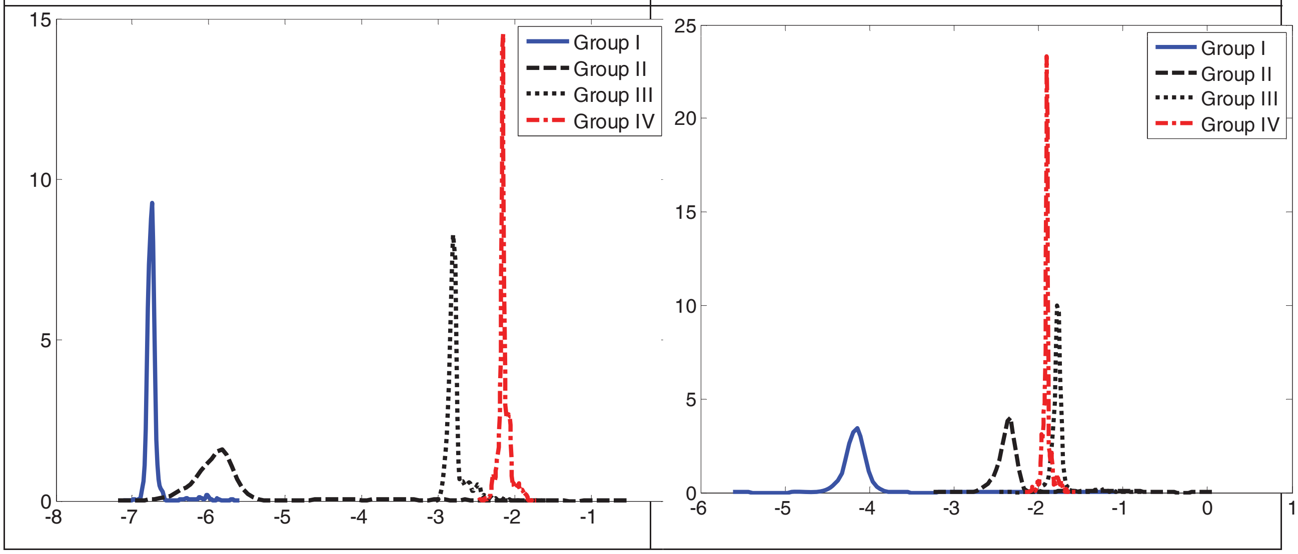
Note - Sender groups: I. Non-resident family members, II. Relatives, III. Friends, neighbors, members of *Iqqub* and *Iddir*, and IV. Church, mosque, NGOs, government organizations.

The main results and the underlying specifications are given in tables 5 and 7 above for static and dynamic versions, respectively.

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

Figure 1. Kernel Distribution of Unobserved Individual Heterogeneity

(a) Dynamic SUR Tobit Model	(b) Dynamic SUR Probit Model



[1] The survey was conducted in collaboration with Economics Department, Addis Ababa University (AAU), and the Centre for the Study of African Economies (CSAE), University of Oxford. The funding for the survey was provided by Economic and Social Research Council (ESRC), Swedish International Development Agency (SIDA), United States Agency for International Development (USAID), and the World Bank. The data are publicly available at various online repositories and web links and detailed description of the survey can be found at http://www.csae.ox.ac.uk/datasets/Ethiopia-ERHS/ERHS-main.html.

An Empirical Analysis of Health Shocks and Informal Risk Sharing Networks

Supplementary Appendices B and C[1]
(Not for publication)

By

Supplementary Appendix B: Theoretical Framework

Following the literature (Thomas and Worrall (1988); Kocherlakota (1996); De Weerdt and Fafchamps (2011)), we provide the theoretical framework for informal risk sharing under limited commitment and derive estimable equation for our empirical analysis.

Under perfect information regime with full commitment, allocation schemes rely on the assumption that contracts are enforceable. However, such arrangement is difficult to implement due to lack of commitment and enforcement mechanisms as individuals may decide to deviate at any given time or state. Such difficulty in enforcement makes the first-best solution of voluntary informal risk sharing arrangement unsustainable (Thomas and Worrall (1988); Kocherlakota (1996)). Sustainable informal risk sharing contracts should, therefore, guarantee lifetime utility of at least the autarky level to voluntarily keep individuals in the risk sharing contract.

Consider a closed economy inhabited by two infinitely-lived identical and risk-averse individuals $i = \{1,2\}$ who maximize lifetime utility. They are identical because they have the same preferences and are endowed with the same exogenous random endowment processes. Let s denote the realized state in period t and s^tdenote the history of endowment processes, i.e. $s^t = (s_1, s_2, \dots, s_t)$. Also, let individual 1 has income $y_1(s_t)$ in state s_t and individual 2 has income $y_2(s_t)$, which are assumed to be independently and identically distributed $(i.i.d.)$ over time with probability $Pr(s_t = s^k) = \pi^k$. Aggregate income in all periods and states is assumed to be constant (i.e., there is no aggregate uncertainty) and is given by $Y = y_1(s_t) + y_1(s_t)$. However, the distribution of income among individuals varies over time depending on the realization of history s^t. Individual i's preference is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t Pr(s^t) u\big(c_i(s^t)\big), \qquad 0 < \beta < 1, \tag{B1}$$

where $c_i(s^t)$ is consumption in period t when history s^toccurs, $Pr(s^t)$ is the probability of history s^t occurring, β is private discount rate, and E is the expectation operator. The utility function $u(\cdot)$ satisfies $u'(\cdot) > 0$ and $u''(\cdot) < 0$ with $lim_{(x\to 0)} u'(x) = \infty$. It is established that risk-averse individuals are better-off involved in a risk sharing arrangement as long as their

[1] Appendix A on additional tables is included in the paper.

endowments are not positively and perfectly correlated. Given that individuals are endowed with riskless asset A_{it} with constant return r, the resource constraint with accumulation is given by

$$\sum_{i=1}^{2} c_{it}(s_t) \leq \sum_{i=1}^{2} [y_i(s_t) + A_{it}(s_t)] = X_t(s_t), \qquad (B2)$$

where $X_t(s_t)$ is total cash in hand. In the presence of limited commitment, individuals voluntarily participate in risk sharing contracts if and only if their lifetime utility from participation is greater than or equal to the autarky level. That is the participation constraint given as follows should hold

$$\sum_{r=1}^{\infty} \beta^{r-1} \Pr(s^r) u\big(c_i(s^r)\big) \geq V_i^{aut}(A_{it}), \qquad (B3)$$

where $V_i^{aut}(A_{it})$ is the value of autarkic life time utility. Then, one can solve the stochastic dynamic model in equation (B1) and (B2) using either a decentralized game approach or a social planner's approach and arrive at the same solution. We follow the latter approach as it is handy to deal with dynamic stochastic game problem. In the social planner's approach, each individual's problem of solving the optimization problem becomes the planner's problem. The social planner maximizes the utility of both individuals by solving the standard stochastic dynamic programming problem given by

$$\max_{c_i} E_0 \sum_{t=0}^{\infty} \beta^t \sum_{i=1}^{2} \omega_i Pr(s^t) u\big(c_i(s^t)\big), \qquad (B4)$$

subject to the resource constraint given in equation (B2) and participation constraints given by equation (B3). Here ω_i such that $\sum_{i=1}^{2} \omega_i = 1$ is the Pareto weight assigned to individuals i. However, due to the participation constraint which depends on future decision values, solving the equation (B1) subject to constraints (B2) and (B3) makes the use of standard stochastic dynamic optimization such as Lagrangian method difficult. However, the Saddle-Point method due to Marcet and Marimon (2011), the optimization problem can be given formulated in a relatively easy to solve Bellman equation formulation. After dropping s^t for the sake of simplicity the problem is to optimize

$$W(A_{it}, \mu_{it}) = \min_{\mu_{it} \geq \mu_{it-1}} \max_{\{c_{it}, A_{it+1}\}_{i=1}^{2}} \Bigg\{ \sum_{i=1}^{2} [(\omega_i + \mu_{it+1}) u(c_{it}) - (\mu_{it+1} - \mu_{it}) V_{it}^{aut}(A_{it})] + \beta E[W(A_{it+1}, \mu_{it+1})] \Bigg\}, \qquad \text{(B5)}$$

subject to the resource constraint in equation (B2) and the co-state (Lagrangian Multiplier on the Participation Constraint) variable μ_{it} whose dynamics is recursively defined as

$$\mu_{it+1} = \mu_{it} + \kappa_{it}, \qquad \mu_{i0} = 0, \qquad\qquad \forall i, t. \tag{B6}$$

The co-state variable is just the sum of past multipliers on the participation constraint. It increases with the number of times the participation constraint binds, where κ_{it} takes a positive value when the constraint binds in period t and 0 otherwise. In the optimization problem given in equation (B5), one can also include individual's Euler equations as additional constraints to guarantee at least the autarkic benefit individuals can get by saving in their assets. However, in the social planner's set-up this constraint become irrelevant at the social planner's Euler equation is always bigger than the individual's (Abraham and Laczo, 2013). For this reason, we ignore individual's storage constraint.

Solving equations (B5), (B2), and (B6) for infinitely-lived agents i and j yields the following Euler equation for Pareto optimal allocations with limited commitment

$$u'(c_{it})(\omega_i + \mu_{it+1}) = u'(c_{jt})(\omega_j + \mu_{jt+1}), \tag{B7}$$

where $u'(\cdot)$ is the marginal utility. In order to derive estimable equation, assume exponential utility function of the form $u(x) = exp(-\rho x)$, where x is money and ρ is risk-aversion parameter. Also, suppose that individual i experiences a negative health shock in period t, then the condition for optimal allocation implies that j should transfer τ_{jit} to i. Then substituting the corresponding budget constraints $c_{jt} = y_{jt} - \tau_{jit}$ and $c_{it} = y_{it} + \tau_{jit}$ yields

$$\tau_{jit} = \left(\frac{y_{jt} - y_{it}}{2}\right) + \frac{1}{2\rho}\ln\left(\frac{\omega_i + \mu_{it+1}}{\omega_j + \mu_{jt+1}}\right), \tag{B8}$$

where τ_{jit} is the amount of transfer from individual j to i. When altruism and social norms enter the model, the resulting Pareto optimal allocation is different. De Weerdt and Fafchamps (2011) extends the standard model to accommodate altruism by assuming that individual j derives subjective utility (V_j) from helping individual i and vice-versa which could be a function of how close (genetically or socially) they are. Then, when the level of altruism is sufficiently large, the promise of future reciprocity becomes irrelevant and altruistic individuals provide assistance when households experience shocks.

Supplementary Appendix C: Estimation Algorithm of Bayesian RE Dynamic Correlated Tobit SUR Model

This appendix describes the estimation algorithm, including computation of the average marginal effects. Combining terms in equations 2 through 5, the dynamic correlated RE Tobit SUR model can be compactly written as

$$\boldsymbol{\tau}^*_{it} = \boldsymbol{\theta}\boldsymbol{W}_{it} + \boldsymbol{u}_i + \boldsymbol{\varepsilon}_{it}, \tag{C1}$$

where $\boldsymbol{\tau}_{it}^* = [\tau_{1it}^*, \tau_{2it}^*, \tau_{3it}^*, \tau_{4it}^*]$, $\boldsymbol{W_{it}} = diag(W_{1it}, W_{2it}, W_{3it}, W_{4it})$, $\boldsymbol{W}_{mit} = [\tau_{mi,t-1},$ $\boldsymbol{X}_{mit}, \tau_{mi0}, \boldsymbol{X}_{mi}]$, $\boldsymbol{\theta} = [\gamma, \boldsymbol{b}, \boldsymbol{\beta}]'$, and all other terms are as defined before. Then, the likelihood function conditional on the latent variables and the covariates can be expressed as

$$f(\boldsymbol{\tau}_{i1}, \dots, \boldsymbol{\tau}_{iT} | \boldsymbol{\tau}_{i1}^*, .., \boldsymbol{\tau}_{Ti}^*, \boldsymbol{W}_{it}, \{\boldsymbol{u}_i\}, \boldsymbol{\theta}, \boldsymbol{\Omega}, \boldsymbol{\Sigma})$$
$$= \prod_{t=1}^{T} \Big\{ 1(\boldsymbol{\tau}_{it} > \boldsymbol{0}) \mathbf{1}(\boldsymbol{\tau}_{it} = \boldsymbol{\tau}_{it}^*) + \mathbf{1}(\boldsymbol{\tau}_{it} = \boldsymbol{0}) 1(\boldsymbol{\tau}_{it}^* < \boldsymbol{0})$$
$$\times \left((2\pi)^{\frac{M}{2}} |\boldsymbol{\Omega}|^{\frac{1}{2}} exp\left\{ -\frac{1}{2} (\boldsymbol{\tau_{it}^*} - \boldsymbol{\theta W}_{it} - \boldsymbol{u_i})' \boldsymbol{\Omega}^{-1} (\boldsymbol{\tau_{it}^*} - \boldsymbol{\theta W_{it}} - \boldsymbol{u_i}) \right\} \right) \Big\}. \quad (C2)$$

The joint posteriors of all parameters of RE dynamic correlated SUR Tobit model is given by

$$p(\{\boldsymbol{\tau}_{it}^*\}, \{\boldsymbol{u}_i\}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{\Omega}, \boldsymbol{\Sigma} | \boldsymbol{\tau}_{i1}, \dots, \boldsymbol{\tau}_{iT}, \boldsymbol{W}_{it})$$
$$\propto \prod_{i=1}^{N} \prod_{t=1}^{T} f(\boldsymbol{\tau}_{i1}, \dots, \boldsymbol{\tau}_{iT} | \boldsymbol{\tau}_{i1}^*, .., \boldsymbol{\tau}_{iT}^*, \boldsymbol{W}_{it}, \{\boldsymbol{u}_i\}, \boldsymbol{\theta}, \boldsymbol{\Omega}, \boldsymbol{\Sigma}) \times p(\{\boldsymbol{\tau}_{it}^*\} | \{\boldsymbol{u}_i\}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{\Omega}, \boldsymbol{\Sigma}, \boldsymbol{\tau}_{i1}, \dots, \boldsymbol{\tau}_{iT}, \boldsymbol{W}_{it})$$
$$\times p(\{\boldsymbol{u}_i\} | \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{\Omega}, \boldsymbol{\Sigma}, \boldsymbol{W}_{it}) \times p(\boldsymbol{u}) \times p(\boldsymbol{\theta})$$
$$\times p(\boldsymbol{\Omega}, \boldsymbol{\Sigma}), \quad (C3)$$

where $p(\cdot)$ are probability distributions. We assign flat (non-informative) priors on all model parameters. The MCMC estimation algorithm for the RE dynamic correlated SUR Tobit model is as follows:

1. For each equation m conditional on τ_{mi0}, $\boldsymbol{W}_{mit}$, $\boldsymbol{u}_i$, u, $\boldsymbol{\theta}, \boldsymbol{\Omega}, \boldsymbol{\Sigma}$ and the latent variables $\tau_{-\mathrm{mit}}^*$, draw τ_{mit}^* from a truncated normal distribution with mean $\boldsymbol{\mu}_{mit}^{\boldsymbol{c}} = \boldsymbol{\theta W}_{mit} + \boldsymbol{u}_{mi} + \boldsymbol{\Omega}_m \boldsymbol{\Omega}_{mm}^{-1} (\tau_{-\mathrm{mit}}^* - \boldsymbol{\theta}_{-m} W_{-mit} - u_{-mi})$ and standard deviation $\sigma_m^{c2} = \boldsymbol{\Omega}_{mm} - \boldsymbol{\Omega}_{mj} \boldsymbol{\Omega}_{mm}^{-1} \boldsymbol{\Omega}_{mj}'$ if $\tau_{mit} = 0$, otherwise set $\tau_{\mathrm{mit}}^* = \tau_{mit}$.
2. Conditional on $\boldsymbol{\tau}_{it}^*$, $\boldsymbol{W}_{it}$, $\boldsymbol{u}_i$, $\boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{\Sigma}$ draw $\boldsymbol{\Omega}$ from inverse Wishart distribution $iw(v_{\boldsymbol{\Omega}}, \boldsymbol{S_\Omega})$ with parameters $v_\Omega = v_{\Omega_0} + NT$and $S_\Omega = S_{\Omega_0} + \sum_{i=1}^{N} \sum_{t=1}^{T} (\boldsymbol{\tau}_{it}^* - \boldsymbol{\theta W}_{it} - \boldsymbol{u}_i)(\boldsymbol{\tau}_{it}^* - \boldsymbol{\theta W}_{it} - \boldsymbol{u}_{\boldsymbol{i}})'$.
3. Conditional on $\boldsymbol{\tau}_{\mathbf{it}}^*$,$\boldsymbol{W}_{it}$, $\boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{\Sigma}$, $\boldsymbol{\Omega}$ draw $\boldsymbol{u}_i$for each individual from multivariate normal distribution $mvn(\boldsymbol{\mu}_{\mathrm{ui}}, \boldsymbol{V}_{ui})$ with mean $\boldsymbol{\mu}_{ui} = \boldsymbol{V}_{ui} (\boldsymbol{\Sigma}^{-1} \boldsymbol{u} + \boldsymbol{\Omega}^{-1} \boldsymbol{W}_i' (\boldsymbol{\tau}_i^* - \boldsymbol{\theta W}_i))$ and variance $\boldsymbol{V}_{ui} = (\boldsymbol{\Sigma}^{-1} + \boldsymbol{\Omega}^{-1} \boldsymbol{l}_T' \boldsymbol{l}_T)^{-1}$.
4. Conditional on $\boldsymbol{u}_i$ and $\boldsymbol{\Sigma}$ draw $\boldsymbol{u}$ **f**rom a multivariate normal distribution $mvn(\boldsymbol{\mu}_u, \boldsymbol{V}_u)$ with mean $\boldsymbol{\mu}_u = \boldsymbol{V}_u \left(\boldsymbol{V}_{\boldsymbol{u_0}}^{-1} \boldsymbol{\mu}_{\boldsymbol{u_0}} + \boldsymbol{\Sigma}^{-1} \sum_{i=1}^{N} \boldsymbol{u}_i \right)$ and variance $\boldsymbol{V}_u = \left(\boldsymbol{V}_{\boldsymbol{u_0}}^{-1} + \boldsymbol{NM\Sigma}^{-1} \right)^{-1}$.
5. Conditional on u_i and u draw Σ from inverse Wishart distribution $iw(v_\Sigma, S_\Sigma)$ with parameters $v_\Sigma = v_{\Sigma_0} + N$ and $\boldsymbol{S_\Sigma} = \boldsymbol{S_{\Sigma_0}} + \sum_{i=1}^{N} (\boldsymbol{u}_i - \boldsymbol{u})(\boldsymbol{u}_i - \boldsymbol{u})'$.

6. **Conditional on** $\boldsymbol{\tau}_{it}^{*}$, $\boldsymbol{W}_{it}$, $\boldsymbol{u}_{i}$, $\boldsymbol{\Omega}$, draw $\boldsymbol{\theta}$ from multivariate normal distribution $mvn(\boldsymbol{\mu_\theta}, \boldsymbol{V_\theta})$ with mean $\boldsymbol{\mu_\theta} = \boldsymbol{V_\theta}\left(\boldsymbol{V}_{\boldsymbol{\theta_0}}^{-1}\boldsymbol{\mu}_{\boldsymbol{\theta_0}} + \sum_{i=1}^{N}\sum_{t=1}^{T}\boldsymbol{W}_{it}\boldsymbol{\Omega}^{-1}(\boldsymbol{\tau}_{it}^{*} - \boldsymbol{u}_i)\right)$ and $\boldsymbol{V_\theta} = \left(\boldsymbol{V}_{\boldsymbol{\theta_0}}^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T}\boldsymbol{W'}_{it}\boldsymbol{\Omega}^{-1}\boldsymbol{W}_{it}\right)$.

The algorithm cycles through steps 1-6 until convergence. We wrote the estimation code in Matlab and tested on simulated data before we apply it to the real data. We conduct 10,000 MCMC simulations with the first 5,000 draws dropped as burn-ins. We assess convergence of the MCMC draws using trace plots as well as formal convergence diagnostic test developed by Geweke (1992).

In order to assess the effect of covariates on transfers, we calculate the Average Partial Effects (APEs). The advantage of the Bayesian method is that APEs can be easily obtained as a byproduct of the MCMC simulations. The predicted values with covariates are given by

$$E(\tau_{mit}|\tau_{-mit}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{W}, \boldsymbol{\Omega}, \boldsymbol{\Sigma}) = \Phi\left(\frac{\mu_{mit}^{c}}{\sigma_m^{c2}}\right)\mu_{mit} + \sigma_m^{c2}\phi\left(\frac{\mu_{mit}^{c}}{\sigma_m^{c2}}\right),$$

where $\mu_{mit}^{c} = u_{mi} + \boldsymbol{\beta}_m\boldsymbol{W}_{mit} + \boldsymbol{\Omega}_{mj}\boldsymbol{\Omega}_{mm}^{-1}(\tau_{-\mathrm{mit}}^{*} - u_{-mi} - \boldsymbol{\beta}_{-m}\boldsymbol{W}_{-mit})$ is the conditional mean, $\sigma_m^{c2} = \Omega_{mm} - \Omega_{mj}\Omega_{mm}^{-1}\Omega'_{mj}$ is the conditional variance. Then, the APEs for the k^{th} continuous variables is given by

$$\frac{\partial E(\tau_{mit}|\tau_{-mit}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{W}, \boldsymbol{\Omega}, \boldsymbol{\Sigma})}{\partial x_{it}^{k}} = \Phi\left(\frac{\mu_{mit}^{c}}{\sigma_m^{c2}}\right)\beta^{k},$$

where $\beta^{k} = \beta_m^{k} - \Omega_{mj}\Omega_{mm}^{-1}\beta_{-m}^{k}$. Similarly, the APE for a dummy variable is given by the difference between the values of $E(\tau_{mit}|\tau_{-mit}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{W}, \boldsymbol{\Omega}, \boldsymbol{\Sigma})$ when $W_{mit}^{k} = 1$ and when $W_{mit}^{k} = 0$, respectively.