Asymmetry of Information within Family Networks

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Abstract

This paper studies asymmetry of information and transfers within 712 extended family networks from Tanzania. Using cross-reports on asset holdings, we construct measures of misperception of living standards among households within the same network. We contrast altruism, pressure, exchange and risk sharing as motives to transfer in simple models with asymmetric information. Testing the model predictions in the data uncovers the active role played by recipients of transfers. Our findings suggest that recipients set the terms of the transfers, either by exerting pressure on donors or because they hold substantial bargaining power in their exchange relationships.

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1 Introduction

Private transfers among extended family members are pervasive in developing countries. A strand of the literature has investigated the determinants of these transfers (see, for example, Rapoport and Docquier (2006) and Cox and Fafchamps (2008)). That literature has, however, typically assumed perfect information about one's income between family members. In contrast, a growing literature on migration suggests that there could be substantial asymmetry of information even among close relatives (McKenzie, Gibson, and Stillman (2012), Seshan and Zubrickas (2015) and Seror (2012)).

Asymmetry of information may matter for private transfers. Using lab experiments in the field to vary the observability of gains, Jakiela and Ozier (2015), in the context of kin and neighbors in rural Kenyan villages, and Ambler (2015), in the context of migrants from El Salvador and their family members at home, show that subjects transfer more when their gains are made public. Seshan and Zubrickas (2015) finds that the more wives of Indian migrants working in Qatar under-estimate the overseas income of their husbands, the lower the share of income sent home as annual remittances. Nyarko, Joseph, and Wang (2015) find remittances from workers in the UAE are strongly correlated with more easily observable variation in earnings. Batista and Narciso (2013) observe higher remittances from a sample of migrants in Ireland when they are offered free phone cards, arguing that it is due to improved information.

This paper uses a unique dataset of 712 extended family networks originating from the Kagera region in Tanzania to study the relationship between the asymmetry of information and private transfers within these networks. Making use of cross-reports on asset ownership among households belonging to the same extended family networks, we measure each household's misperceptions about the living standards of the other households in its network. We then explore and contrast altruism, pressure, exchange and risk sharing as motives to transfer. Under these competing explanations, models of inter-household transfers with asymmetry of information yield predictions about the correlations between misperceptions and transfers after controlling for the income of the two parties, as well as the correlations between incomes and transfers after controlling for misperceptions. We refer to these as 'partial' correlations. Taking these predictions to the data, we find that transfers co-move with both the donor's actual and perceived living standards, but not with the recipient's actual or perceived living standards. This is consistent with a relationship where the recipients have power and request transfers from the donor, either using pressure to give or in exchange of services.

Our paper makes a number of contributions. First, our paper provides a coherent and generally applicable approach to measuring asymmetric information through surveys. In many environments of interest, household income is generated from smallholder farming or informal non-agricultural businesses and a large share of consumption is home-produced. In such contexts, measuring self-reported household income is problematic (Deaton (1997)), so we should not expect to be able to measure perceptions of income by others. In contrast, questions on asset holdings are common in household surveys and provide an attractive indicator of medium term standards of living. Furthermore, eliciting beliefs from respondents about asset holdings of others can be done at low cost in linked surveys.

The question arises, though, of how to translate households' beliefs about the various assets holding of others into measures of households' beliefs regarding the living standards of others. We propose a measure of misperception that consists of a weighted sum of differences between believed and actual asset holdings. The weights are set depending on how these particular assets predict per capita consumption in the population. This, thus, captures the percentage by which a household overestimates, or underestimates when negative, the per capita consumption of another household.

Our second contribution is descriptive. Applying this method to the data allows us to give a complete characterization of the asymmetry of information among the 712 Tanzanian extended family networks. Not surprisingly, we find a substantial level of asymmetry of information and show that it correlates positively with genetic, social and physical distance between households. However, there is no systematic underestimation or overestimation: perceptions are, on average, correct.

Our third contribution is to relate transfers to misperceptions by developing simple theoretical models of transfers with asymmetry of information regarding recipient and donor income. We develop static models that contrast three possible motives for transfers: altruism, in which the potential donor cares about the recipient; pressure, in which the recipient has some means of imposing a utility cost on the donor; and exchange, in which the transfer represents a payment for some good or service provided by the recipient.[1] Our model of altruism predicts a negative partial correlation of transfers with both the recipient's actual income *and* the donor's misperception of that income. A model of exchange in which the donor has all the bargaining power and risk-sharing motives also predict a negative partial

[1] In addition, we consider the implications of a dynamic risk sharing model with asymmetry of information. However, since our measures of misperception are based on assets, it is better suited to capture asymmetry of information regarding medium term standard of living, rather than asymmetry of information regarding short term income shocks.

correlation between the transfer and the recipient's income. In contrast, if the driving motivation is pressure or exchange in which the recipient has all the bargaining power, it is the donor's income and the recipient's misperception of the donor's income that matter and are positively correlated with the transfers. Note that these predictions capture not only the effect of information on transfers, but also the feedback mechanisms whereby transfers themselves, or the amount requested, are informative.

The data suggest that recipients of transfers play an active role in their relationship with donors. Rather than being passive, recipients seem to set the terms of transfers, either by exerting pressure to give on donors or by holding the bargaining power during an exchange of services. With respect to policy, this implies that we should probably worry less about possible crowding out effects of public transfers, and more about inefficiencies due to the cost of pressure and the moral hazard that can result from it (Alger and Weibull (2008)). This is consistent with the recent experimental evidence of Jakiela and Ozier (2015), Ambler (2015), Boltz, Marazyan, and Villar (2015) and Squires (2016), and the large ethnographic literature highlighting the importance of disapproval, shaming, ostracism and other means of pressure, as described and cited in Platteau (2012) and Chort, Gubert, and Senne (2012).

The rest of the paper is organized as follows. Section 2 presents the data on extended family networks in Tanzania that we use to build the measures of asymmetric information. These measures are defined and validated in Section 3. Section 4 presents competing models of transfers. Section 5 studies the correlations between transfers and misperceptions of income to examine the empirical validity of the models and Section 6 concludes.

2 Data

This paper uses the 2010 wave of the Kagera Health and Development Survey (KHDS).[2] Kagera, in the north-western part of Tanzania, has a population of 2.5 million people, the vast majority of whom engage in agriculture. The Kagera region is relatively isolated: it borders landlocked countries Uganda, Rwanda and Burundi and is 1,400 km away from the main port and commercial capital, Dar es Salaam. Using these data, De Weerdt (2010) and Beegle, De Weerdt, and Dercon (2011) have shown that the diversification of income generating activities and migration are key household strategies for growth.

KHDS 2010 attempted to trace all individuals belonging to households that were surveyed

[2]The field work was implemented in 2010 by Economic Development Initiatives (EDI). A full description of the fieldwork and data can be found in De Weerdt et al. (2012).

in the original survey KHDS 1991-94. The latter interviewed 915 households in 52 villages representative of the Kagera Region over four rounds from 1991 to 1994. KHDS 2010 searched for any individual listed in any household roster in KHDS 1991-94 and interviewed households in which these individuals were found residing in 2010. The survey attained very high recontact rates. Out of the original 915 households there are only 71 households (8%) where not a single individual was traced (excluding 26 households where all members had died). The interviewing team accounted, in 2010, for 88% of the 6,353 individuals listed on any KHDS 1991-94 roster: 68% of the original respondents were visited and surveyed, while 20% of respondents were confirmed to have died. 12% of individuals were not found. Out of the interviewed individuals 45% lived in the baseline village, 53% had migrated within the country, 2% to another East African country (primarily Uganda) and 0.3% had left East Africa.

Practically, we take advantage of this unique data structure to define a *split-off household* as any household that contains at least one member from the original roster (from KHDS 1991-94) and an *extended family network* as a network of split-off households, all originating from the same baseline household.[3]

Note that the location of a household surveyed in 2010 depends strongly on the original member's role in the original household. We find that 58% of households who host the household head 18 years after baseline still live in the baseline village, as compared to only 22% of the other households in the family networks. The latter moved more frequently to nearby villages (17% of them versus 6% of households with former head) or to elsewhere in Kagera (41% of them versus 19% of households with former head). Moreover, split-off households with daughters of the former head are less likely (21%) to live in baseline village than split-off households with sons (30%), a reflection of patrilocal marriage customs.

In addition to a detailed questionnaire regarding their own consumption [4] and asset holdings, we designed survey questions regarding the asset holdings and relative standing of the other households in their network, as well as questions about the interactions and transfers between their household and each of the other households in their network. For example, if the original members have split into three different households, the network consists of these

[3] De Weerdt and Hirvonen (2015) study how consumption co-moves across linked nodes in these networks.

[4] The questionnaire included extensive food and non-food consumption modules. The final consumption aggregate includes purchased and home-produced food, as well as food eaten outside of the household. It contains 51 food items and 27 non-food items. The aggregates are temporally and spatially deflated using data from a price questionnaire included in the survey. Consumption is expressed in annual per capita terms using 2010 Tanzanian shillings. A full description of the consumption aggregate is available at *http://www.edi-africa.com/research/khds/introduction.htm*.

three households and each household is asked questions about the other two, giving us a data set of 6 dyadic observations. Having data on both sides of each pair of linked households in the networks allows us to contrast the beliefs held by one household about the other with the reality as recorded in the questionnaire.

After dropping households that did not split or have missing or incomplete interviews, our 'large' sample consists of 3,173 households from 712 extended family networks, yielding 13,808 unique within-family pairwise combinations of households. Some of the asymmetric information questions were skipped for split-off households residing in the same location as the respondent. Wherever the analysis below makes use of these skipped questions, we revert to our 'small' sample: a subsample of 9,032 dyads, all living in different locations, and encompassing 2,807 households within 613 extended family networks. Tables 11 and 12 in Appendix provide summary statistics on these samples.

The survey collected data on amounts remitted, both in-kind and cash. Over two thirds of households in our sample report remitting in the year preceding the survey. The average amount of cash remitted, among those who did, was USD 35, representing, on average, 7% of consumption per capita and 2% of total household consumption for the remitting households. That average masks a wide distribution, with the top decile remitting USD 160, or 8% of their total household consumption. Out of these transfers, 59% goes to recipients within the extended family network.

In empirical applications networks are typically self-defined, with questionnaires probing each respondent for a list of network partners in the sense of friendship or households to whom one can ask help or borrow money from. Our network definition is different as it is based on membership in a household 18 years ago. Our definition has the advantage of being objectively defined, not subject to recall and the definition of a link is not based on the existence of transfers. Attrition aside, we would have complete networks defined in this way alleviating econometric concerns related to sampled networks (Chandrasekhar and Lewis (2011)). However, despite the tracking success of KHDS 2010 we have some attrition that is likely to be non random. The principal strategy for tracing people from the original KHDS household rosters was to obtain their contact details through interviewed relatives. Not surprisingly, attrition rates are higher among households that have infrequent contact with their family members. Thus, we are likely looking at a somewhat more connected set of family members.[5]

[5] Out of all dyads in our larger sample 53% communicated at least once in the month preceding the survey, while for 5% the last communication was over 5 years ago (within the smaller sample 41% of dyads communicated within the past month and 7% within the past year). By contrast, the reports from interviewed

Table 1: Asymmetric information.

	Underestimate	**Spot-on**	**Overestimate**	**DK**
Completed O'level	0.029	0.920	0.022	0.029
Has formal job	0.054	0.872	0.008	0.066
Owns house	0.088	0.748	0.095	0.068
Owns land	0.120	0.761	0.048	0.071
Owns livestock	0.059	0.745	0.072	0.123
Owns phone	0.096	0.725	0.075	0.105
Owns TV	0.080	0.720	0.044	0.156
Owns motorized vehic	0.040	0.667	0.142	0.151

Notes: Comparing actual realizations to beliefs held by extended family members. Cells indicate the proportion of observations. Completed O'level means having completed the first four (out of six) years of secondary education. N=9,032.

3 Quantifying Asymmetry of Information

3.1 Beliefs about assets, education and employment

We can measure the extent to which extended family members are (mis)informed about each other by cross-checking the beliefs of any household i about educational attainment, employment and asset ownership of household j with the information in household j's questionnaire. We can do this over 8 different items listed in Table 1.[6] Household i can underestimate, correctly estimate or overestimate the status of household j; household i could also answer that it does not know the educational attainment, employment status or assets owned by household j. Table 1 gives frequencies of these cross-reports: most underestimates of assets occur with respect to land and phones, while most overestimates occur with respect to vehicles. Educational attainment and employment have the most correct perceptions. Note, however, that very few people overestimate the employment position of their relatives, while relatively more underestimate (i.e. think their family members do not have a formal job, while in fact they do).

households about untraced households (which constitute dyads that are dropped from the analysis) show that only 26% of such pairs communicated within the last month and 23% over 5 years ago. Our main empirical results also hold for dyads that did not communicate recently, giving some credence that attrition - in as far as it relates to the strength of communication between network member - is not a major concern.

[6] Perceptions of educational attainment and occupation were collected for each original panel member (i.e. individuals who were member of the baseline household) currently member of j. The perceptions on the 6 assets were asked at the j-household level.

Ultimately, we are interested in measuring what i's perception on these 8 items tells us about i's perception of j's standard of living, and to what extent and in which direction i misperceives j's true standard of living. A naive measure of asymmetry of information would be the simple sum of perceptions on the 8 items above adding up overestimates (set to $+1$), underestimates (set to -1), correct responses (set to 0) and don't know responses (set to 0). However, this approach has a number of problems. First, it assumes that all items carry the same weight in the measure. Second, it assumes that the weight of each item is separable from the household's characteristics, and from other items. Third, it assumes that all items signal something positive about the individual's living standards. An example of a violation of these last two assumptions would be if livestock ownership signals high income for rural households, but low income for urban households. In the next section we alleviate these concerns with a novel measure of asymmetric information: a weighted sum of misperceptions and their interactions, with weights set according to the correlations of the perceived items with household per capita consumption in the population.

3.2 Perceived Consumption and Misperceptions

Let $\mathbf{A}_j$ denote the profile of actual ownership of assets, education and occupation for household j, including any relevant interaction effects among assets, education and occupation. This is the profile over which i expresses beliefs $\mathbf{B}_{ij}$. In addition, let $\mathbf{X}_j$ be a vector of basic characteristics of household j that we would think are public knowledge among relatives.

Given i's belief about the profile of ownership of j, what can we infer about i's estimate of j's consumption? The view that we take here is that by observing households around him, i has learned the joint distribution of ownership profiles $\mathbf{A}_j$ and household per capita consumption c_j conditional on household characteristics $\mathbf{X}_j$ and $\mathbf{A}_j$.

Hence, we first estimate a consumption regression among our households

$$ln(c_j) = \boldsymbol{\alpha}\mathbf{A}_j + \boldsymbol{\beta}\mathbf{X}_j + \boldsymbol{\gamma}\mathbf{A}_j\mathbf{X}_j + \epsilon_j \tag{1}$$

where c_j is the actual per capita consumption for household j. See Section 3.3 for more information on how we estimate equation (1).

Retrieving the coefficients estimated $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ from (1), we can then use the characteristics $\mathbf{X}_j$ and i's beliefs about j's assets $\mathbf{B}_{ij}$ to construct measures of i's perception of j's consumption. Let

$$ln(C_{ij}) = \boldsymbol{\alpha}\mathbf{B}_{ij} + \boldsymbol{\beta}\mathbf{X}_j + \boldsymbol{\gamma}\mathbf{B}_{ij}\mathbf{X}_j. \tag{2}$$

How does $ln(C_{ij})$ relate to i's beliefs regarding j's log per capita consumption? The answer depends on what knowledge i has of the unobservables ϵ_j in equation (1). We consider two extreme assumptions regarding i's knowledge of ϵ_j and use it to construct two alternative measures of i's perception of j's consumption. One benchmark is to think that households are much better informed than we are about all unobservable characteristics, including temporary shocks, that affect the income of their relatives. Hence, at the one end of the spectrum, we can assume that j's relatives are perfectly informed of ϵ_j, in which case i's perceived consumption for j is

$$P_{ij} = \ln(C_{ij}) + \epsilon_j.$$

In this case, if household i held perfect knowledge on household j's assets then the predicted consumption would equal the actual consumption.

An alternative benchmark is to posit that household i uses only $\mathbf{X}_j$ and her beliefs about j's assets $\mathbf{B}_{ij}$ in forming her estimate of household j's per capita consumption $\mathbf{C}_{ij}$. This assumes that household i has no additional information about household j, over and above $\mathbf{X}_j$, so that i's perceived consumption for j is

$$P'_{ij} = \ln(C_{ij}).$$

We believe that the truth lies somewhere in between these two estimates.

This method implicitly assumes that any information that i has received about j is captured in ϵ_j or in $\mathbf{B}_{ij}$, and therefore does not have an independent effect on i's perception of j's consumption. For example, the transfers that j has given to i or the frequency with which j calls i can provide information to i regarding j's standard of living. We assume that this information is fully reflected in i's beliefs about j's assets and therefore in i's perception of j's consumption. This approach accounts for the possibility that one could make a number of mistakes regarding a relative's assets and still have a fairly accurate estimate of his household per capita consumption. It is entirely possible that a person, when answering the survey questions about her relatives, reports beliefs on assets that are consistent with her perception of the relative's consumption. She might report that her relative has a TV but no phone, while her relative has a phone but no TV, but if both asset ownership profiles correspond to similar lifestyle (per capita consumption) in the overall population it amounts to the same perceived consumption.

Using these two benchmarks, we can create the following two measures of misperceptions – the difference between i's perceived consumption for j and j's actual consumption:

$$\Omega_{ij} = P_{ij} - ln(c_j) = (\mathbf{B}_{ij} - \mathbf{A}_j)\,\alpha + \boldsymbol{\gamma}\,(\mathbf{B}_{ij} - \mathbf{A}_j)\,\mathbf{X}_j, \text{ and} \tag{3}$$

$$\Omega'_{ij} = P'_{ij} - ln(c_j) = (\mathbf{B}_{ij} - \mathbf{A}_j)\,\alpha + \boldsymbol{\gamma}\,(\mathbf{B}_{ij} - \mathbf{A}_j)\,\mathbf{X}_j - \epsilon_j. \tag{4}$$

Our measure of misperception Ω_{ij} is a weighted sum of the difference in believed and actual occupation, education and assets. Thus, it is well suited to measure misperceptions of medium-term living standards, rather than asymmetry of information regarding temporary shocks. In contrast, Ω'_{ij} might measure not only misperceptions on medium term living standards, but also be affected by beliefs regarding temporary shocks, which are part of ϵ_j. For example, a temporary positive consumption shock to j, $\epsilon_j > 0$, with constant $\mathbf{A}_j$ will lower Ω'_{ij} – making it more likely for us to conclude that i underestimates j's lifestyle – but will not affect our measurement of Ω_{ij}.

The log specification conveniently implies that Ω_{ij} is a good approximation of the percentage by which i overestimates ($\Omega_{ij} > 0$) or underestimates ($\Omega_{ij} < 0$) j's consumption.

3.3 Measuring Weights for Perceived Consumption

To determine which variables to consider for the weights we proceed as follows. There are 12 variables that we can reasonably assume to be known by other family members and therefore be part of $\mathbf{X}_j$. These are the gender, age and squared age of the household head, eight indicator variables capturing the household's age-sex composition and a dummy indicating whether the household resides in rural or urban area. For $\mathbf{A}_i$, we consider in their level form the 8 asset variables for which we have beliefs questions: educational attainment, employment and the ownership of the six assets listed in Table 1. Then all 12 common knowledge variables are interacted with each other, all 8 asset variables are interacted with each other and all $12 * 8$ interactions across both sets are made. This gives us a total of 190 interactions and 20 level variables to consider.

We want to remain agnostic about which of these 210 variables should enter the prediction regression and turn to approximately sparse regression models to ensure variables are selected with a view to good out-of-sample forecasts. In the Least Absolute Shrinkage and Selection Models (LASSO) of Frank and Friedman (1993) and Tibshirani (1996), the parameters are chosen in such a way to minimize the sum of least squares plus a term that penalizes additional variables. We use the post-LASSO estimator of Belloni et al. (2012), which proceeds in two steps. In a first step, the LASSO procedure is used to select all variables with non-zero weight. In a second step, the weights in the beliefs regression are determined by taking the coefficients from an OLS regression that uses only the variables selected in the first step.[7]

Table 2 reports the final weights. Of the 8 candidate asset variables, only one, livestock ownership, did not get selected. In other words, livestock (by itself and in the various interacted forms it was considered) did not correlate sufficiently with per capita consumption once other variables were controlled for. Half of the 12 common knowledge variables were dropped in levels and only 5 interaction terms were retained. The final regression explains 57% of the total sample variation with 17 variables and a constant.

Note that when predicting household i's beliefs about household j, we need to decide how to treat "don't know" (DK) answers to the assets, educational attainment and employment questions. We take the conservative approach of replacing DKs with location-specific sample means, depending on whether household j lives in an urban or rural area. We also control for the number of DK answers in the regressions in Sections 3.4 and 5.

Applying the weights from Table 2 to Equation (3) and (4), we can calculate Ω and Ω', for each ij pair. Figure 1 shows kernel density estimations for both measures. The mean (standard deviation) is 0.006 (0.315) for Ω and 0.002 (0.532) for Ω'. Figure 1 also shows 95% confidence intervals around the sample means. These were obtained through the bootstrap procedure described in Appendix 1. They are [-.013,.027] and [-.020,.023] for Ω and Ω' respectively. This means that there is no indication of any systematic overestimation or underestimation of others' standards of living.

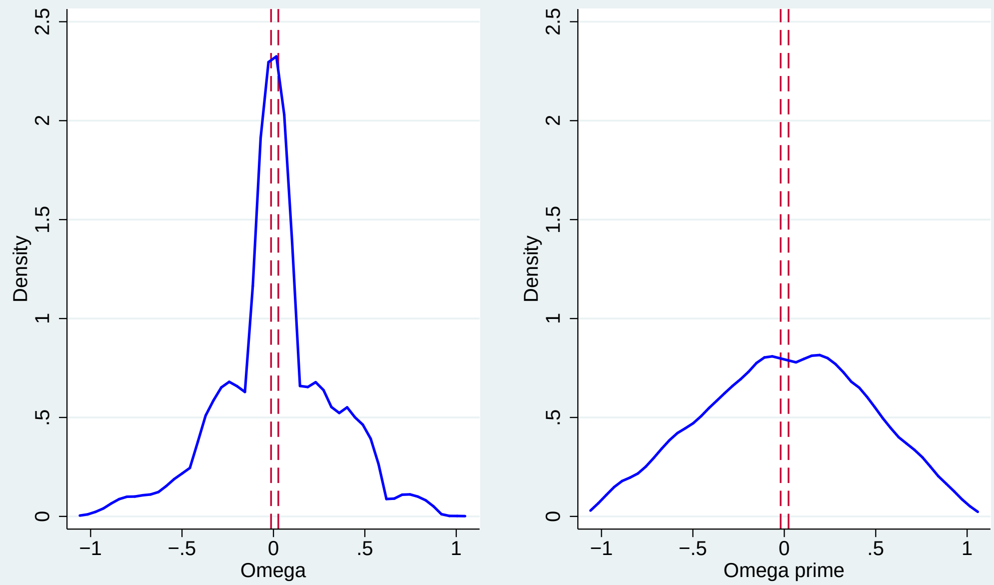
However, there is significant asymmetry of information. The average of the absolute values of Ω and Ω' are 0.21 and 0.42, meaning that people are, on average, 21 and 42 per cent mistaken, respectively. The kernel smoother from Figure 1 obfuscates the fact that Ω equals exactly zero in 30% of dyads, where all guesses were correct. The Ω' distribution does not exhibit this lumping at zero because it subtracts the ϵ_j term in its calculation. For the same reason the distribution of Ω' has a much larger spread than that of Ω.

[7] We implemented the procedure using the LassoShooting ado file made available by Christian Hansen on his homepage here $http://faculty.chicagobooth.edu/christian.hansen/research/$.

Table 2: Weights in Ω

	Coefficient
Completed O'level	0.161**
	(2.190)
Has formal job	0.185***
	(5.620)
Owns house	-0.264***
	(-4.223)
Owns phone	0.300***
	(15.492)
Owns TV	0.240**
	(2.060)
Owns vehicle	0.272***
	(3.833)
Owns phone * Completed O'level	0.079
	(0.996)
Owns TV * Owns phone	0.085
	(0.716)
Owns vehicle * Owns house	0.207***
	(2.716)
Age of hh head * Owns house	0.004***
	(2.764)
Age of hh head * Owns land	0.001
	(0.847)
Urban	0.160***
	(7.701)
Age of hh head	-0.009***
	(-5.423)
Males 0-5 years	-0.216***
	(-17.926)
Males 6-15 years	-0.103***
	(-10.459)
Females 0-5 years	-0.214***
	(-17.632)
Females 6-15 years	-0.099***
	(-9.862)
Constant	13.466***
	(237.160)
Adjusted R-squared	0.565
N	3173

Notes: Final weights in Ω Variables selected with LASSO. t statistics between brackets under the coefficient. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



Notes: The dashed vertical lines represent 95% confidence intervals around the mean
The point estimates of these means are .006 for Omega and .002 for Omega prime
30% of Omega observations = 0.
X−axis truncated to span −1 to +1 for better rendition.
Bandwidth=0.06.

Figure 1: Distribution of Ω and Ω' (N=9,032)

3.4 Validation

We first validate Ω and Ω' by comparing them with a completely different measure of asymmetric information. For each of its network partners, any household i was asked to imagine a nine-step ladder where the top of the ladder, step 9, represents the best possible life and the bottom, step 1, represents the worst possible life. Household i was then asked to rank each household j in his network on the ladder. Table 3 shows that, using household i fixed effects, if household i places household j higher on the ladder, controlling for household j's actual consumption, then Ω_{ij} and Ω'_{ij} are higher. That is, for 2 relatives with the same actual consumption, household i's misperception of their standards of living is highly correlated with where he differentially places each on the ladder. The strong correlations between our misperception measures and these subjective perceptions give us confidence that Ω and Ω' are indeed capturing latent beliefs. When testing the model in Section 5 we will use the ladder as an alternative measure of misperceptions to verify the robustness of the results.

We further validate our misperception measures by verifying how they co-vary with variables that measure the fluidity of information flows between the two nodes. It is very natural

Table 3: Comparing Ω to subjective perceptions.

	Ω_{ij}	Ω'_{ij}
i places j on bottom 3 rungs of 9-step ladder	-0.071***	-0.108***
	(-7.016)	(-8.903)
i places j on top 3 rungs of 9-step ladder	0.101***	0.225***
	(4.993)	(9.264)
i gives DK answer to ladder question regarding j	-0.041**	-0.064***
	(-2.327)	(-3.037)
log of j's actual consumption per capita	-0.130***	-0.582***
	(-21.878)	(-81.738)
Constant	1.758***	7.722***
	(22.274)	(81.602)
N	9032	9032

Notes: Household i fixed effect regression of Ω and Ω' on 3 ladder dummies indicating where household i places household j on a 9-step ladder. Regressions control for the number of don't know responses to the asymmetric information questions that each side of the dyad gave.

to expect individuals who are closer to each other, physically or socially, to have better information about each other. Table 4 relates misperceptions to a number of proximity variables through probit regressions. In the first column, the dependent variable is whether Ω_{ij} is zero, which requires that all the beliefs of i regarding j are correct and occurs in 30% of all dyads. In the second column, the dummy is whether Ω'_{ij}, which is never exactly zero, is close to 0 in the sense that it falls in $[-0.5\sigma, +0.5\sigma]$ where $\sigma = 0.532$ is the standard deviation of Ω' (39% of all dyads).

In line with our expectations we see that the accuracy of perceptions, and in particular as measured by Ω_{ij}, increases with proximity variables such as kilometers of geographic distance between the households, whether a parent-child link exists across the two households, whether they communicated in the past 2 years and whether they recently shared a meal together. This is also consistent with the findings of Alatas et al. (2016) in Indonesian networks. We also see that there is less accurate information about extended family members living in urban areas, controlling for distance travelled.

Table 4: Correct expectations and distance.

	$\Omega_{ij} = 0$	$\Omega'_{ij} \approx 0$
Distance between HHs (100 km)	-0.0089***	-0.0040**
	(-7.916)	(-2.413)
j located in urban area	-0.0708***	-0.0176
	(-10.221)	(-1.549)
Parent-child link	0.0178**	0.0008
	(2.207)	(0.055)
i and j communicated in the past 2 years	0.0214**	-0.0161
	(2.165)	(-0.967)
Number of years since i and j last lived together	0.0013**	0.0017*
	(2.314)	(1.691)
Shared at least one meal in the past month	0.0091	0.0401**
	(0.995)	(2.326)
N	9032	9032
Percent of observations with LHS = 1	27%	39%

Notes: Probit regressions of correct expectations. Marginal effect reported. t statistics in brackets under the coefficient. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions also control for the number of don't know responses to the asymmetric information questions that each side of the dyad gave and an indicator variable for 36 missing km distance observations.

4 Model of Misperceptions and Transfers

In this Section, we present simple models relating income, misperceptions of income and transfers. First, we model the three possible motivations for transfers in a static context: altruism, exchange and pressure. Then, we consider a dynamic model model of risk sharing with asymmetry of information. For each model, we derive predictions regarding the correlation between income, misperceptions and transfers.

Preferences and Income:

Consider two individuals, a recipient R and a donor D. A first possible motive for transfers is altruism: the donor cares not only about her own utility of consumption, but also about the recipient's. Denote by $u_i(c)$ the utility of consumption of $i \in \{R, D\}$, with the usual properties that $u' > 0$ and $u'' < 0$, and denote by $\alpha_D \in [0, 1)$ D's altruism, that is the weight that the donor puts on the recipient's utility of consumption (following Becker (1974)).[8]

[8]See also Stark (1995).

The recipient R and donor D's utilities are then $v_R = u_R(c_R)$ and

$$v_D = u_D(c_D) + \alpha_D \mathbb{E}_D u_R(\widetilde{c}_R) \tag{5}$$

where $\widetilde{c}_R$ is R's consumption as perceived by D. Note that we could easily assume that the recipient is also altruistic towards the donor.

Income and Information:

We assume that R and D's actual incomes are private information, though the following income distributions are common knowledge. The donor D's income y is either low (L) with a probability $1 - q_D$ or high (H) with a probability q_D, $L < H$ and $q_D \in (0, 1)$. The recipient R's income x takes a low value (ℓ) with probability $1 - q_R$ or a high value (h) otherwise, $\ell < h$ and $q_R \in (0, 1)$.

Let $i \in \{R, D\}$ be one party and $j \neq i \in \{R, D\}$ be the other. Individual i's beliefs about j's income are based on j's actual probability of having a high income, but will also reflect any information about the actual realization of j's income that i receives. Assume that i receives a signal $s_j \in (0, 1)$ about j's income m drawn from the conditional distribution $f_j(s|m)$. The realization of the signals is common knowledge. We assume that the conditional distributions satisfy the monotonic likelihood property, so that high values of the signal are relatively more likely when income is higher, but also that at the extreme, these signals are almost perfectly informative:

$[S1]$ $\frac{f_R(s|h)}{f_R(s|\ell)}$ and $\frac{f_D(s|H)}{f_D(s|L)}$ are strictly increasing in s,
$[S2]$ $\lim_{s\uparrow 1} \frac{f_R(s|\ell)}{f_R(s|h)} = \lim_{s\uparrow 1} \frac{f_D(s|L)}{f_D(s|H)} = 0$ and $\lim_{s\downarrow 0} \frac{f_R(s|h)}{f_R(s|\ell)} = \lim_{s\downarrow 0} \frac{f_D(s|H)}{f_D(s|L)} = 0$.

After using the signals and Bayes rule to update their beliefs, the posterior beliefs that the recipient and the donor hold about each other are given by

$$\begin{aligned} \pi^R_{s_R} &= \frac{q_R f_R(s_R|h)}{q_R f_R(s_R|h) + (1 - q_R) f_R(s_R|\ell)} \textit{ and} \\ \pi^D_{s_D} &= \frac{q_D f_D(s_D|H)}{q_D f_D(s_D|H) + (1 - q_D) f_D(s_D|L)}, \end{aligned}$$

where π^j_s is the probability that the other party assigns to j having a high income after observing signal s.

Pressure: There is a large literature describing the pressure under which many households in developing countries find themselves to transfer to relatives (see Chort, Gubert, and Senne (2012) and Platteau (2012) among others).

To model this pressure motive, we assume that R can commit on imposing a punishment, a utility cost $p \in [0, P]$, on D. The nature of this punishment is likely to differ from household to household. There may be ways in which retaliation or feelings of guilt or shame can be directly meted out to someone who does not transfer enough. Similar punishments, but also loss of social status could be imposed indirectly through the community (see Cox and Fafchamps (2008)). Pressure might be available only at certain times, for instance when the recipient has a well-known need (such as suffering from some observable shock, or because school fees are due).

Exchange: Finally, another possible motive for transfers, in particular for migrants, is quid-pro-quo. As discussed by Cox and Fafchamps (2008) and Rapoport and Docquier (2006), private transfers might be given in exchange for goods or services provided by the recipient. This could be help with young children, old-age support or maintaining property rights for migrants. Assume that, at times, the recipient is in position to provide a service of utility value v to the donor at a utility cost c.

Altruism

Consider first a situation in which altruism is driving the transfers: $\alpha_D > 0$, $P = 0$ and $v = 0$. The recipient R has no credible way to signal her income. Hence, for a given realization of her income y and the signal $s_R = s$, D chooses to make a transfer t to R that maximizes

$$u_D(y - t) + \alpha_D[\pi_s^R u_R(h + t) + (1 - \pi_s^R) u_R(\ell + t)]. \tag{6}$$

If interior, D's choice of transfer t^* strictly increase on his own income y and decreases in π_s^R, his posterior beliefs regarding R's income. Hence, the altruism model predicts a positive correlation between transfers and the donor's actual income, and a negative correlation between transfers and the donor's perception of the recipient's income. The latter implies a negative correlation between transfers and the donor's misperception of the recipient income controlling for the actual income and a negative correlation between transfers and the recipient's income controlling for the donor's misperception. Since there is a one-to-one correspondence between the donor's income and the transfer that she chooses when a positive transfer is made, upon receiving a transfer, R would know D's realized income. Hence, no correlation is predicted between the transfers and the recipient's misperception of the donor's income.[9]

[9]The same predictions would apply if the recipient was also altruistic towards the donor. This is also the finding of Barczyk and Kredler (2014) in a dynamic and continuous time context. In addition, if they

Pressure

Now, let's study the case without altruism $\alpha_D = 0$ and without services $v = 0$, but in which transfers are driven by the possibility of pressure: $P > 0$. Since the cost for D of making a given transfer is decreasing in her income, R can make use of pressure not only to receive a transfer but also to get D to reveal her real income.

Indeed, given his income x, R offers a menu to D of transfers t and contingent pressure $p(t)$:
− a transfer of T_H or more implies no pressure;
− a transfer of T_L implies pressure $\underline{p}$; and
− any other transfer is associated with pressure $\overline{p}$.

The offer is designed so that the donor chooses to give T_H and faces no pressure when her income is high, while she chooses to give T_L and faces pressure $\underline{p}$ when her income is low.

Incentive constraints: To simplify notation, denote by $V_y(T)$ D's utility if her income is y and she makes a transfer T:

$$V_y(T) = u_D(y - T). \tag{7}$$

The incentive constraints for both type H and type L to comply with the offered menu are

$$\begin{aligned} V_H(T_H) &\geq \max_t \{V_H(t) - p(t)\} && (8) \\ V_L(T_L) - \underline{p} &\geq \max_t \{V_L(t) - p(t)\} && (9) \end{aligned}$$

where $p(t)$ is the pressure triggered by the scheme. D's preferred transfer to R is 0 while R would like to receive as much as possible. Hence, R uses the highest pressure as a threat $\overline{p} = P$ and, if D has a low income, her preferred deviation would be to make no transfer.

It follows that the incentive constraint for type L in (9) becomes,

$$V_L(T_L) - \underline{p} \geq V_L(0) - P. \tag{10}$$

Now, for type H, the relevant constraint ensures that H does not want to pretend to be L:[10]

$$V_H(T_H) \geq V_H(T_L) - \underline{p}. \tag{11}$$

care about each other's total utility (and not just each other's utility of consumption) then an interesting signaling game among donors arise as shown in Genicot (2016). However, if the degree of altruism of the donor was not known to the recipient, then there could be a positive correlation between the transfers and the recipient's misperception of the donor's income controlling for the donor's income.

[10] As usual, (10) and (11) imply that $V_H(T_H) - \underline{p} \geq V_H(0) - P$. This is shown in Appendix 2.

Given his income x and a signal s, the recipient R chooses $\underline{p}$, T_H and T_L to maximize

$$\pi_s^D u_R(x + T_H) + (1 - \pi_s^D) u_R(x + T_L) \tag{12}$$

subject to (10) and (11).

The following two types of offer (or contracts) are possible:

Pooling: R asks D to transfer at least t^p in which case no pressure is applied $\underline{p} = 0$, otherwise the maximal pressure $\overline{p} = P$ would be applied. Hence, D makes the same transfer irrespective of her income $T_L = T_H = t^p$. Beliefs are therefore not updated and R never learns D's real income. The transfer t^p is such that a type L donor is indifferent between giving t^p and receiving the maximum amount of pressure, i.e. $u_D(L - t^p) = u_D(L) - P$.

or

Separating: R demands from D either a transfer of T_H in exchange for no pressure, or a lower transfer $T_L(< T_H)$ but with some pressure $\underline{p} > 0$. Any other transfer would result in maximal pressure. D chooses to transfer more when her income is high $T_H > T_L$ but she is subject to pressure $\underline{p} > 0$ when her income (and transfer) is lower. Since D's transfer varies with her income, R updates his beliefs and has full information ex-post. The exact values T_H, T_L and $\underline{p}$ depend on the probabilities π_s^D and on x.

The higher R's belief that D has a high income, the more likely he is to offer a separating contract. This intuition is formalized in Proposition 1 whose proof is in Appendix 2.

Proposition 1 *There is a cutoff value of the signal $\widetilde{s} \in (0, 1)$ such that R offers a pooling contract if $s_D \leq \widetilde{s}$ and R offers a separating contract if $s_D > \widetilde{s}$ with T_H (T_L) increasing (decreasing) in s.*

Proposition 1 tells us that either:
(i) $s_D > \widetilde{s}$ and R offers a separating contract, in which case D gives a low transfer if her actual income is low but is subject to pressure while she gives a high transfer and receive no pressure if her actual income is high. R's beliefs are correct ex-post; or
(ii) $s_D \leq \widetilde{s}$ and R offers a pooling contract with transfer $t^p > T_L$, in which case R overestimates (underestimates) D's income ex-post if D was low (high).

Table 7 illustrates these findings. First, there is a positive correlation between D's actual income and her transfer to R. Second, for a given income level of D (H or L) there exists a positive correlation between the perception of D's income by R (π^D) and the transfer from D to R: the more R thinks D has, the higher the transfer from D to R is.

Table 5: Summary of the Pressure Model

D's income	Signal	Contract to D	Transfers to R*	Ω_{RD}
L	$s_D > \widetilde{s}$	separating	low (T_L)	$= 0$ (correct)
	$s_D \leq \widetilde{s}$	pooling	medium (t^p)	> 0 (overestimate)
H	$s_D > \widetilde{s}$	separating	high (T_H)	$= 0$ (correct)
	$s_D \leq \widetilde{s}$	pooling	medium (t^p)	< 0 (underestimate)

$*\ T_L < t^p < T_H$

In terms of the recipient's income, whether a higher x affects the contract offered and, if so, whether it encourages separating or pooling depends on the utility function. In any case the correlation between the recipient's income and the transfers is small and unlikely to be significant.[11] Finally, controlling for the recipient's income, and therefore the actual offer, variation in the donor's ex-post beliefs about the recipient stems from receiving different signals under a pooling offer. This has no bearing on transfers so that, controlling for incomes, there is no correlation between transfers and the donor's misperceptions.

Exchange

To study the exchange motive, assume that there is no pressure ($P = 0$) nor altruism ($\alpha_D = 0$), but that the recipient can provide a service of utility value v to the donor at a utility cost c, $c < v$. The price of that service, the transfer, clearly depends on their relative bargaining power.

Denote as $\underline{t}(x)$, the lowest transfer that the recipient would accept to provide the service, given his income x:

$$u_R(x + \underline{t}(x)) - u_R(x) = c, \tag{13}$$

and as $\bar{t}(y)$, the highest transfer that a donor with income y would pay for the service:

$$u_D(y) - u_D(y - \bar{t}(y)) = v. \tag{14}$$

We assume that the relative value of the service (v/c) is sufficient that the exchange is

[11] If the recipient utility function exhibits diminishing risk aversion then the recipient may be more likely to offer a separating contract when his income is high ($\widetilde{s}$ decreases) and, for any given signal s_D above the threshold, R may ask a higher T_H and a lower T_L when his income is high. Since a higher spread between T_L and T_H must come with a slightly higher mean transfer, this could imply a small positive correlation between the transfers and the recipient's income.

socially optimal: $\bar{t}(L) > \underline{t}(h)$. We follow Cox and Fafchamps (2008) and Rapoport and Docquier (2006) and consider in turn the two extremes: the case where the donor has all the bargaining power and the case where the recipient has all the bargaining power.

Exchange-D: Donor has the bargaining power

Assume that D gets to make a take-it-or-leave-it offer to R. This recipient's reservation price $\underline{t}(x)$ is clearly increasing in his income x. Hence, D essentially chooses between a) offering $\underline{t}(h)$ for the service, an offer that R always accepts, or b) offering a lower transfer $\underline{t}(\ell)$ that R accepts only when his income is low. Other offers are dominated. The optimal choice depends on D's income y and her beliefs regarding R's income π_s^R. D chooses a) if

$$\begin{aligned} & u_D(y-\underline{t}(h))+v \geq \pi_s^R u_D(y)+(1-\pi_s^R)(u_D(y-\underline{t}(\ell))+v) \Leftrightarrow \\ & v \geq [u_D(y)-u_D(y-\underline{t}(h))]+\frac{1-\pi_s^R}{\pi_s^R}[u_D(y-\underline{t}(\ell))-u_D(y-\underline{t}(h))], \end{aligned} \tag{15}$$

and chooses b) otherwise. Higher π_s^R makes this inequality more likely to hold. For low values of the signal s_R, π_s^R is close to 0 and inequality (15) cannot hold, while for high values of the signal s_R, π_s^R is close to 1 and (15) is necessarily satisfied.

Proposition 2 *There is a cutoff value of the signal $\bar{s} \in (0,1)$ such that D offers $\underline{t}(\ell)$ if $s_R \leq \bar{s}$ and D offers $\underline{t}(h)$ if $s_R > \bar{s}$.*

D offers $\underline{t}(\ell)$ when she receives a signal that the recipient's income is likely to be low ($s_R \leq \bar{s}$), and she offers $\underline{t}(h)$ when the signal indicates that recipient's income is likely to be high $s_R > \bar{s}$. Controlling for D's perception of R's income, the actual transfer is negatively correlated with R's actual income. And controlling for the actual realization of R's income (x), the correlation between the transfer and D's perception of R's income (π^R) is ambiguous: it is positive for low values of x and negative for high values of x.

Table 6: Summary of Exchange-D scenario [3]

R's income	Signal	Offer to R	Transfers to R*	Ω_{DR}
ℓ	$s_R > \bar{s}$	$\underline{t}(h)$	$\underline{t}(h)$	> 0 (overestimate)
	$s_R \leq \bar{s}$	$\underline{t}(\ell)$	$\underline{t}(\ell)$	$= 0$ (correct)
h	$s_R > \bar{s}$	$\underline{t}(h)$	$\underline{t}(h)$	< 0 (underestimate)
	$s_R \leq \bar{s}$	$\underline{t}(\ell)$	0	$= 0$ (correct)

What about the donor's income y? A higher income makes inequality (15) more likely to hold. Richer donors are more likely to offer the high price $\underline{t}(h)$ so that the threshold $\overline{s}$ is smaller for richer donors. This implies a positive correlation between transfers and donor's income. This correlation is likely to be small as it comes only from the realization of the signal that reveals y's income: the realizations of the signal s_R that lies between the threshold $\overline{s}$ for $y = H$ and the threshold $\overline{s}$ for $y = L$. Controlling for the actual income of the donor, only the signal that the recipient receives affects his beliefs about the donor's income so that there is no correlation with the transfers.

Exchange-R: Recipient has the bargaining power

Now, assume that the recipient gets to make a take-it-or-leave-it offer to the donor. It is easy to check that the donor's reservation price $\overline{t}(y)$ too is increasing in her income. Hence, R essentially chooses between two options: a) demanding $\overline{t}(L)$ for the service, an offer that D always accepts, or b) demanding a higher transfer $\overline{t}(H)$ that D rejects when her income is low but accepts when her income is high. Other demands would be dominated by one of these two options. R's chosen option depends on his income x and his beliefs about D's income π_s^D. R chooses a) if

$$
\begin{aligned}
&u_R(x + \overline{t}(L)) - c \geq \pi_s^D (u_R(x + \overline{t}(H)) - c) + (1 - \pi_s^D) u_R(x) \Leftrightarrow \\
&[u_R(x + \overline{t}(L)) - u_R(x)] - c \geq \frac{\pi_s^D}{1 - \pi_s^D} [u_R(x + \overline{t}(H)) - u_R(x + \overline{t}(L))], \qquad (16)
\end{aligned}
$$

and chooses b) otherwise. We see that when π_s^D is close to 0, inequality (16) is satisfied while it fails for value of π_s^D close to 1. The higher π_s^D is the more likely R is to ask $\overline{t}(H)$.

Proposition 3 *There is a cutoff value of the signal $s^* \in (0, 1)$ such that R asks $\overline{t}(L)$ if $s_D \leq s^*$ and R asks $\overline{t}(H)$ if $s_D > s^*$.*

R asks $\overline{t}(L)$ when he receives a signal that the donor's income is likely to be low, and he offers $\overline{t}(H)$ when the signal indicates that donor's income is likely to be high. Controlling for D's income (y), the transfer is positively correlated with R's perception of D's income (π_s^D) and, controlling for R's perception of D's income, the transfer is positively correlated with D's income.

Again, there will be a correlation between the recipient's income x and the transfers only for the signal values for which if it affects the scenario that R chooses. Hence, this effect should

Table 7: Summary of Exchange-R scenario [3]

D's income	Signal	Demand to D	Transfers to R^*	Ω_{RD}
L	$s_D > s^*$	$\bar{t}(H)$	0	$= 0$ (correct)
	$s_D \leq s^*$	$\bar{t}(L)$	$\bar{t}(L)$	> 0 (overestimate)
H	$s_D > s^*$	$\bar{t}(H)$	$\bar{t}(H)$	$= 0$ (correct)
	$s_D \leq s^*$	$\bar{t}(L)$	$\bar{t}(L)$	< 0 (underestimate)

be small. As a higher income for the recipient could make him more or less likely to select a) depending on the values of $\bar{t}(L)$ and $\bar{t}(H)$ and on his utility function, this correlation, if there is one, could go in any direction. Controlling for R's actual income x, only the signal about it causes variation in D's beliefs about R's income and this is uncorrelated with the transfers.

Risk Sharing

So far, we have considered only static models of transfers. That focus is, to some extent, due to the KHDS data on which our empirics are built. We do not have repeated data on consumption per capita for our households and we measure misperceptions through cross-reports on assets. It is nevertheless worth briefly discussing risk sharing.

Imagine that our two individuals draw an income realization in each period. For simplicity, assume away the signal. Instead individuals send messages to each other regarding the realization of their income. The prescribed transfers depend on these reports as well as the history of previous reports. Under the constrained optimal risk sharing scheme (see Cole and Kocherlakota (1999), Attanasio and Pavoni (2011), Cole and Kocherlakota (1999), Kinnan (2009) and Hauser and Hopenhayn (2008) among others), the prescribed transfers and continuation utilities must be such that individuals truthfully reveal their income and there are no misperceptions left. Although the prescribed transfer from a donor to a recipient is history dependent,[12] transfers are increasing in the income realization of the donor and decreasing in the income realization of the recipient. Assuming that the effect of the difference in average income between these individuals (see Genicot (2006)) is small – this effect is absent for instance in the case of log utility – the prediction that transfers are increasing in the income realization of the donor and decreasing in the income realization of the recipient would hold even without controlling for the average income of the individual.

[12]Incentive compatibility requires the transfer to decrease with recent claims from the recipient.

Predictions

Table 8 summarizes the predicted *partial* correlations between transfers, donor's and recipient's income, and misperception under the four motives. That is, it shows the predicted correlations between the transfers and the donor's (recipient's) misperception controlling for the income realizations and the other's misperception, and the predicted partial correlation between the transfers and the donor's (recipient's) income controlling for the misperceptions and the other's income. These correspond to the predictions regarding the regression coefficients in the next section. Importantly, the misperceptions concern ex-post beliefs, so that these correlations take into account the feedback mechanisms through which transfers influence beliefs.

We made two decisions for the table. First, some misperceptions in the data are likely due to measurement errors/noise. Hence, when the model predicts no misperception at all and therefore no correlation could be calculated, we enter 0. If the misperceptions are just due to noise then one would expect a zero correlation. Second, recall that in the pressure and exchange-R models, the partial correlation between the transfers and R's income are likely to be small as it exists only when the type of contract chosen by R changes with his income, and in addition the overall effect averages some positive and negative effects.[13] Hence, we enter ϵ in Table 8 for these effects.

Table 8: Predictions

Partial correlation between transfer and: Model	Ω_{RD}	Ω_{DR}	D's income	R's income
Altruism	0	$-$	$+$	$-$
Pressure	$+$	0	$+$	ϵ_+
Exchange-D	0	A	$+$	$-$
Exchange-R	$+$	0	$+$	ϵ
Risk Sharing	0	0	$+$	$-$

Notes: A= ambiguous ; ϵ_+ small non negative effect ; ϵ small ambiguous effect.

Finally, note that if the opportunity presents itself, households might hide some of their income.Access to a hiding technology would result in an increase in the precision of a high signal and reduce the prediction of a low signal. Hence, the existence of a (partial) hiding technology would not affect our main predictions, though it would attenuate some of the effects. Similarly, access to a costly monitoring would not affect the predicted correlations.[14]

[13] Under decreasing risk aversion, though small the overall effect would be positive under the pressure model but ambiguous in the exchange-R model.

[14] See de Laat (2014) for evidence of split household members engaging in costly monitoring.

5 Asymmetric information and transfers

This section tests the predictions from Table 8 regarding the partial correlations between transfers (T_{RD}) received by any household R in the family network from any other family D in the same network and (i) the degree of misperceptions of the recipient about the donor (Ω_{RD} or Ω'_{RD}), (ii) the degree of misperceptions of the donor about the recipient (Ω_{DR} or Ω'_{DR}), (iii) the donor's living standards (I_D) and (iv) the recipient's living standards (I_R). Living standards are proxied by log consumption per capita.

We estimate these partial correlations through dyadic regressions of T_{RD}, whether or not D reported giving transfers to R in the year preceding the survey,[15] on the four correlates that we are interested in. This brings with it a number of econometric challenges. The first is that we need to condition the correlations on the correct variables in order to get unbiased estimates. In the model, we assume everything constant across both donor and recipient. We can implement this empirically by using a two-way fixed effect model, which includes a fixed effect for R and D, α_R and α_D, respectively.[16] While this does not capture any dyadic specific heterogeneity that may cloud these correlations, we also control for a set of observable dyadic characteristics describing the relationship between donor and recipient households to minimize such concerns.

Our preferred regression then is:

$$T_{RD} = \beta_1 \Omega_{RD} + \beta_2 \Omega_{DR} + \mathbf{P}_{RD}\gamma_1 + \alpha_R + \alpha_D + \epsilon_{RD}, \tag{17}$$

where ϵ_{RD} is an error term and $\mathbf{P}_{RD}$ is a vector of variables describing the relationship between the R-D household pair. This includes whether the heads of both households share the same religion or tribe, whether a child or parent relationship links both households, the geographic distance between the two households and the number of DK responses to the asymmetric information questions each side of the dyad gave.

A second econometric issue arises from the fact that Ω and Ω' are predicted values, which means that standard parametric approaches will overstate the precision with which they are measured. We therefore present bootstrapped standard errors, calculated through the two-step procedure described in Appendix 1.

One of the variables of interest from the model predictions in Table 8 is D's standard of living

[15] 25% of dyads have $T_{RD} = 1$

[16] These models have been discussed by Mittag (2012), with De Weerdt (2004) providing an early application of two-way fixed effects in dyadic regressions for network analysis.

I_D, which is subsumed in the fixed effect α_D. To retrieve an estimate of the coefficient of I_D, we drop α_D in Equation (17) and replace it with the natural logarithm of D's consumption and other characteristics of D. We estimate:

$$T_{RD} = \beta_1 \Omega_{RD} + \beta_2 \Omega_{DR} + \beta_3 I_D + \mathbf{P}_{RD}\gamma_1 + \mathbf{Z}_D\gamma_2 + \alpha_R + \epsilon_{RD}, \tag{18}$$

where $\mathbf{Z}_D$ is a vector of household D characteristics including the sex, age and years of education of the household head, whether the household owns a phone or a motorized vehicle (as these may serve to lower the cost of transfers), as well as the number of household members that fall in each of eight exclusive and exhaustive age-sex categories (this controls for household size).

Similarly, to retrieve an estimate on the I_R variable we drop α_R in Equation (17) and replace it with R's consumption and other characteristics:

$$T_{RD} = \beta_1 \Omega_{RD} + \beta_2 \Omega_{DR} + \beta_4 I_R + \mathbf{P}_{RD}\gamma_1 + \mathbf{Z}_R\gamma_2 + \alpha_D + \epsilon_{RD}. \tag{19}$$

We can determine T_{RD} in two ways. First, we can use what R reports receiving from D in the incoming gifts section of his questionnaire. Alternatively, we can use what D reports giving to R in the outgoing gifts section of her questionnaire. When we run the two-way fixed effects regressions, we report the results both ways. When we omit one of the fixed effects, we use the report from the questionnaire of whoever's fixed effect is still included, i.e. when we drop the donor fixed effect, we use the recipient's report of transfers in. The advantage of this approach is that the controls Z are measured independently from the transfer measure used on the left hand side of the equation since they are sourced from a different questionnaire. Each regression table will show in the heading not only which equation is being estimated, but also whether the transfers used on the left hand side are from the questionnaire of R or D.

It is worth recalling that we do not attach a causal interpretation to these coefficients. In fact, the model explicitly allows for feedback mechanisms between the level of transfers and perceptions. For example, in a separating equilibrium, a high T_{RD} will cause beliefs Ω_{RD} to be revised upwards. We use the dyadic regression set-up as a convenient way to retrieve the partial correlations, measured by β_1, β_2, β_3 and β_4, in order to compare their signs to the predictions from Table 8.

We estimate Equations (18) and (19) separately for both Ω and Ω'. Equation (17) is only reported for Ω, since, as can be seen from Equations (3) and (4) above, the difference between

Ω and Ω' is subsumed in the double fixed effect and, in consequence, the regression results for both measures are identical. All equations are estimated using linear probability models.

Table 9: Main Results, Partial correlations with transfers: Ω and income

Equation No.	**(17)**	**(17)**	**(18)**	**(19)**	**(18)**	**(19)**
Transfer report	*R*	*D*	*R*	*R*	*D*	*D*
Ω_{RD}	0.075***	0.090***	0.081***		0.056***	
	(0.029)	(0.030)	(0.020)		(0.020)	
Ω_{DR}	0.036	0.011	0.033		0.026	
	(0.028)	(0.030)	(0.021)		(0.019)	
Ω'_{RD}				0.118***		0.056***
				(0.018)		(0.020)
Ω'_{DR}				0.032		0.012
				(0.021)		(0.017)
I_D			0.040***	0.141***		
			(0.011)	(0.019)		
I_R					0.007	0.017
					(0.010)	(0.018)
R^2	0.72	0.72	0.09	0.10	0.11	0.11
N	9032	9032	9032	9032	9032	9032

Notes: Fixed effect linear probability models with bootstrapped standard errors in parentheses under the coefficient. Each column heading indicates, in brackets, the equation being estimated and below that, italicized, whether the left-hand side transfer variable is reported by R or D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N=9032.

The picture that emerges from this table is clearly that $\beta_1 > 0$, $\beta_2 = 0$, $\beta_3 > 0$ and $\beta_4 = 0$, which is consistent with either pressure or exchange-R in Table 8.[17] From the first and second columns we see that when Ω_{RD} goes up with one standard deviation (=0.315), then, depending on the specification, the likelihood of a transfer goes up by two to three percentage points, which represents 11% to 14% of the prevalence of transfers among dyads. The absence of a negative coefficient on the the recipient's income, β_4, allows us to reject both altruism and exchange-D as motives of transfers. We can also reject the hypothesis that β_2, the coefficient on Ω_{DR}, is smaller than zero, thus rejecting a second prediction of the altruism model.

[17] To identify dyads with potentially larger means of pressure or bargaining power in the hands of the recipient, we also interacted the income of the Donor and the perceptions of the donor income with an indicator of whether the donor household hosts a child of Recipient household. The interaction with Donor's income is significant and positive, suggesting extra power of the recipient household in this type of parent-child relationship. We thank one of our referees for this suggestion.

The absence of negative correlation between transfers and the recipient's income is consistent with the finding of Lucas and Stark (1985) and Cox, Eser, and Jimenez (1998) who reject altruism as a motive for remittances among migrants in Botswana and as a motive for transfers in Peru. In contrast, Kazianga (2006) finds some support for the altruistic motive among the middle income class in Burkina Faso, but not for low income levels, and in the US, Altonji, Hayashi, and Kotlikoff (1997) finds a negative correlation between in-vivo transfers and the recipient's income in support of the altruism remittance motive.

We can check that our findings are unaltered if we use different measures of the perceptions of standard of living, coming from the ladder questions described in Section 3.4. We run slightly different versions of Equations (17), (18) and (19), where we include a measure for whether i places j on the lowest steps 1, 2 or 3 of the ladder, $\underline{L}_{ij}$, or the highest steps 7, 8, 9 of the ladder, $\overline{L}_{ij}$. Furthermore, the variables measuring the number of don't know responses to asymmetric information questions are replaced by two dummy variables indicating that don't know responses were given to the ladder questions by the donor or the recipient, respectively. The two way fixed-effects version then becomes:

$$T_{RD} = \delta_1 \underline{L}_{RD} + \delta_2 \overline{L}_{RD} + \delta_3 \underline{L}_{DR} + \delta_4 \overline{L}_{DR} + \mathbf{P}_{RD}\gamma_1 + \alpha_R + \alpha_D + \epsilon_{RD}. \tag{20}$$

Unlike the Ω variables, these ladder questions are not predicted values, but are directly reported in the questionnaire. We do not bootstrap the standard errors here, but still need to allow for correlations between transfers received by the same recipient or sent by the same donor to avoid biased estimates of the standard errors. We use the non-nested two-way clustering approach developed by Cameron, Gelbach, and Miller (2011) and implemented in Stata by Baum, Shaffer, and Stillman (2007)[18] with clustering on both R and D.

The FE specification allow us to capture any fixed unobserved characteristic of the recipient or of the donor, which may systematically affect their relative perceptions of the positions of other households in their family network. As above, to retrieve estimates of the coefficients on I_D and I_R, we estimate

$$T_{RD} = \delta_1 \underline{L}_{RD} + \delta_2 \overline{L}_{RD} + \delta_3 \underline{L}_{DR} + \delta_4 \overline{L}_{DR} + \mathbf{P}_{RD}\gamma_1 + \beta_3 I_D + \mathbf{Z}_D\gamma_2 + \alpha_R + \epsilon_{RD} \tag{21}$$

and

$$T_{RD} = \delta_1 \underline{L}_{RD} + \delta_2 \overline{L}_{RD} + \delta_3 \underline{L}_{DR} + \delta_4 \overline{L}_{DR} + \mathbf{P}_{RD}\gamma_1 + \beta_4 I_R + \mathbf{Z}_R\gamma_2 + \alpha_D + \epsilon_{RD}. \tag{22}$$

[18]An alternative method is provided by Fafchamps and Gubert (2007)

Table 10: Partial correlations with transfers: ladder and income

Equation No. **Transfer report**	**(20)** *R*	**(20)** *D*	**(21)** *R*	**(22)** *D*
R places D low on ladder ($\underline{L}_{RD}$)	-0.052***	-0.025*	-0.082***	-0.015*
	(0.016)	(0.015)	(0.011)	(0.009)
R places D high on ladder ($\overline{L}_{RD}$)	-0.006	-0.033	0.043*	-0.019
	(0.034)	(0.032)	(0.025)	(0.020)
D places R low on ladder ($\underline{L}_{DR}$)	-0.015	0.000	-0.005	0.005
	(0.016)	(0.015)	(0.010)	(0.011)
D places R high on ladder ($\overline{L}_{DR}$)	-0.003	-0.040	-0.013	-0.029
	(0.030)	(0.035)	(0.019)	(0.022)
I_D			0.034***	
			(0.009)	
I_R				0.005
				(0.009)
R^2	0.64	0.64	0.09	0.10

Notes: Fixed Effect Linear probability models. Cluster-robust standard errors are in parentheses under the coefficient, with clustering on both R and D. Each column heading indicates, in brackets, the equation being estimated and below that, italicized, whether the left-hand side transfer variable is reported by R or D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $N = 13,808$.

Table 10 shows the estimates of these three equations. As above we use the transfer report from the questionnaire of whoever's fixed effect is still included. We show results both ways for the double fixed effect. To be consistent with the results above, we would expect to see that, controlling for D's actual consumption (through either α_D or I_D), lower perceptions of R about D's standard of living are correlated with a lower likelihood of transfers from D to R, which implies $\delta_1 < 0$ and, symmetrically, that higher perceptions of R about D's standard of living are correlated with a higher likelihood of transfers from D to R, that is $\delta_2 > 0$. As before, we expect $\delta_3 = 0$, $\delta_4 = 0$, $\beta_3 > 0$ and $\beta_4 = 0$. Table 10 does yield this pattern, except for the estimated coefficients δ_2 which turn out to be largely not significantly different from zero at conventional levels. This anomaly could be attributed to the fact that this category holds only 5% of the observations. However expanding the boundaries does not make a difference. Taken together, these results support the main results indicating that the power in the gift-giving relationship lies with the recipient of the transfer, consistent with either a pressure model or an exchange model in which the recipient holds the bargaining power.[19]

6 Conclusion

This article analyzed how private transfers between linked households relate to actual and perceived living standards. To do this, we built novel measures of asymmetric information that compare actual to perceived asset holdings. We applied these measures to original survey data on households belonging to 712 extended family networks in Tanzania. Using rich information on their relationships and characteristics, we validated our measures of misperceptions of living standards and showed that the degree of misperception increases with genetic, social and physical distance between households. We found, on the one hand, substantial asymmetry of information within our extended family network, but on the other hand that perceptions are correct on average.

We then developed simple static models to predict the correlations between income, misperceptions of income and transfers depending on whether it is altruism, exchange or pressure that is the main driver of transfers. We showed that the predictions of these models differ. In particular, when the recipient plays an active role (either in a model of pressure to give or in a model of exchange in which the recipient holds all the bargaining power), transfers have a positive partial correlation to the donor's actual income and to the recipient's misperception of that income (a positive value of misperceptions indicating over-estimation of income). In contrast, when transfers are motivated by pure altruism of the donor, their partial correlation to the income of the recipient and to the misperception of it by the donor are negative. Finally, the recipient's income is negatively correlated to transfers under an exchange model in which the donor holds the bargaining power.

Our data support a model of pressure to give or a model of exchange in which the recipient holds substantial bargaining power. These results highlight the active role played by recipients of transfers in our setting and show that it is possible to disentangle some motives of transfers using cross-sectional household survey data on linked households.

[19] The on-line appendix shows that these results remain robust under a number of alternative specifications such as using the extensive margin of transfers (value), using proxies for pre-transfer incomes, including dyads living in the same location (large sample) and using discrete choice modeling to relax the assumptions underlying the linear probability model.

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Appendix 1: Bootstrap Procedure

In step 1, we start from our sample of $3,173$ households and draw, with replacement, a new bootstrap sample of equal size. For each bootstrap sample we run regression Equation 1 and coefficients $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$, as well as the error term ϵ_j. In step 2 we start from our sample of $9,032$ dyads and draw, with replacement, a new bootstrap sample of equal size. The sampling of dyads in step 2 is independent of the sampling of households in step 1. We then apply the values of $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ and ϵ_j calculated in step 1 to recalculate Ω and Ω' for all dyads. We run the regression for which we require bootstrapped standard errors, using this new sample and these new estimates Ω and Ω'. We collect, for each of 1000 different bootstrap samples, the regression coefficients of interest and report their standard errors across the 1000 replicates.

The 95% confidence intervals on the first moments of the distributions of Ω and Ω' are calculated in the same way, except that 1000 averages are collected and the 2.5 and 97.5 percentiles across the replicates of the mean are used as the lower and upper cut-offs of the confidence interval.

Appendix 2: Proofs

Model of Pressure

We can rewrite the incentive constraint for type L in (10) as

$$u_D(L) - u_D(L - T_L) \leq P - \underline{p}. \tag{23}$$

It follows then directly from the concavity of u_D that

$$u_D(H) - u_D(H - T_L) \leq P - \underline{p},$$

so that, if (23) holds a donor of type H would prefer pretending to be a low type than make zero transfer and receive full pressure. It follows that the relevant constraint for type H is not to want to pretend to be a low type (11). We can rewrite this constraint as

$$u_D(H - T_L) - u_D(H - T_H) \leq \underline{p}. \tag{24}$$

Given his income x and the signal s received, the recipient R chooses $\underline{p}$, T_H and T_L to maximize

$$\pi_s^D u_R(x + T_H) + (1 - \pi_s^D) u_R(x + T_L) \tag{25}$$

subject to (23) and (24).

Denoting as λ and μ the Lagrange multipliers on (23) and (24) respectively, the first order conditions tell us that

$$\begin{aligned} \pi_s^D u_R'(x + T_H) &= \mu u_D'(H - T_H) &(26)\\ (1 - \pi_s^D) u_R'(x + T_L) &= \lambda u_D'(L - T_L) - \mu u_D'(H - T_L), &(27) \end{aligned}$$

and that $\lambda = \mu$ if $\underline{p} \in (0, P)$, while $\underline{p} = 0$ if $\mu < \lambda$ and $\underline{p} = P$ if $\mu > \lambda$.

Proof of Proposition 1

Assumption S1 implies that π_s^D is increasing in s, while Assumption S2 implies that π_s^D tends to 0 when s tends to 0 and π_s^D tends to 1 when s tends to 1.

For values of the signal s close to 0, π_s^D is close to 0. Equations (26) and (27) imply then that μ is close to 0 while λ is strictly positive. It follows that $\underline{p}$ must be 0 and $T_L = T_H$. The recipient offers a pooling contract. It is obvious from the objective that higher values of the signal gives incentive to raise T_H and to lower T_L, thereby making a separating contract more likely. When the signal s takes values close to 1, $(1 - \pi_s^D)$ and therefore the left hand side of (27) is close to 0. Since $u_D'(L - T_L) > u_D'(H - T_L)$ for any $T_L > 0$, it must be that $\mu > \lambda$. Hence, $\underline{p} = P$ and $T_L = 0$.

Thus, there is a cutoff value of the signal $\widetilde{s} \in (0, 1)$ that is such that R offers a pooling contract if $s_D \leq \widetilde{s}$ and R offers a separating contract if $s_D > \widetilde{s}$ with T_H (T_L) increasing (decreasing) in s.

Appendix 3: Summary statistics

Table 11: Summary statistics of household variables

	Mean	**SD**
Log consumption per capita	13.12	0.70
Urban	0.34	0.47
Completed O'level	0.13	0.33
Has formal job	0.09	0.28
Owns house	0.75	0.43
Owns land	0.87	0.34
Owns livestock	0.12	0.33
Owns phone	0.60	0.49
Owns TV	0.19	0.39
Owns vehicle	0.09	0.29
Head is male	0.80	0.40
Age of hh head	41.04	15.14
Males 0-5 years	0.50	0.71
Males 6-15 years	0.60	0.87
Males 16-60 years	1.07	0.73
Males 61+ years	0.08	0.27
Females 0-5 years	0.49	0.70
Females 6-15 years	0.61	0.86
Females 16-60 years	1.11	0.74
Females 61+ years	0.11	0.33

Notes: $N = 3,173$.

Table 12: Summary statistics of dyadic variables

	Sample $N = 9,032$		**Sample** $N = 13,808$	
	Mean	**SD**	**Mean**	**SD**
D reports giving gift to R in past 12 months	0.20	0.40	0.24	0.42
Ω_{RD}	0.01	0.32	0.01	0.31
Ω_{DR}	0.01	0.32	0.01	0.31
Ω'_{RD}	0.00	0.53	-0.00	0.53
Ω'_{DR}	0.00	0.53	-0.00	0.53
R places D low on ladder ($\underline{L}_{RD}$)	0.41	0.49	0.42	0.49
R places D high on ladder ($\overline{L}_{RD}$)	0.05	0.21	0.04	0.21
R answers DK on ladder question about D	0.11	0.31	0.09	0.28
D places R low on ladder ($\underline{L}_{DR}$)	0.41	0.49	0.42	0.49
D places R high on ladder ($\overline{L}_{DR}$)	0.05	0.21	0.04	0.21
D answers DK on ladder question about R	0.11	0.31	0.09	0.28
I_R	13.19	0.72	13.13	0.69
R HH head is male	0.82	0.39	0.81	0.39
R HH head age	39.93	14.22	40.51	14.77
R HH head years education	6.74	3.27	6.40	3.23
R HH No. Males 0-5 years	0.49	0.69	0.51	0.71
R HH No. Males 6-15 years	0.60	0.87	0.62	0.89
R HH No. Males 16-60 years	1.08	0.74	1.07	0.71
R HH No. Males 61+ years	0.06	0.25	0.07	0.26
R HH No. Females 0-5 years	0.49	0.69	0.50	0.70
R HH No. Females 6-15 years	0.60	0.86	0.62	0.87
R HH No. Females 16-60 years	1.12	0.74	1.12	0.75
R HH No. Females 61+ years	0.10	0.31	0.11	0.32
i has phone	0.66	0.47	0.61	0.49
i has vehicle	0.12	0.32	0.11	0.31
Parent-child link	0.17	0.38	0.22	0.41
km distance	214.07	339.40	150.51	295.71

Appendix 4: Robustness Tests

Robustness checks using linear models

We conduct the following robustness checks.

First, so far, we have only looked at the extensive margin, as we believe that measurement errors are less likely to plague reports on whether a transfer took place than on their exact value. On the other hand, if that concern was unfounded, the intensive margin of transfers would contain more information. Table 13 show that our results are robust to using the value of the transfers.

Second, one may worry about spurious correlation between transfers and incomes since transfers out are not consumed by the donor (diminishing her income, as proxied by total consumption) and transfers in may contribute to the consumption of the recipient. Even though we do not know what the counterfactual consumption would be in the absence of transfers, we deal with this to some extent in Table 14 by subtracting transfers from the recipient's consumption and adding transfers to the donor's consumption to build proxies for pre-transfer income.

Third, while we have information on ladder estimates for people living in the same location, we do not have information on their assets and therefore no Ω estimate. One way to deal with this would be to assume perfect information for these dyads and place their Ω values to 0. The results of this exercise are given in Table 15.

The results from these three robustness checks are in line with our main results.

Robustness to discrete choice modeling

One shortcoming of the LPM model is that it makes extreme assumptions on the distributions of the error terms, which are likely to be violated in the case of a discrete outcome. To check for robustness we first use the conditional logit model of Chamberlain (1980), which provides consistent Fixed Effect estimators of the parameters $\beta_1, \beta_2, \beta_3$ and β_4 displayed in equations (18) and (19) when the outcome considered is discrete.

The results presented in columns (1) and (2) for Ω and in columns (5) and (6) for Ω' of Table 16 are qualitatively very similar to our main results in Table 9, which is reassuring.

In line with our models of pressure or exchange with recipient having full bargaining power,

Table 13: Table 9 using transfer values

Equation No.	**(17)**	**(17)**	**(18)**	**(19)**	**(18)**	**(19)**
Transfer report	R	D	R	R	D	D
Ω_{RD}	0.807***	0.758***	0.816***		0.488**	
	(0.266)	(0.273)	(0.181)		(0.190)	
Ω_{DR}	0.273	0.116	0.271		0.253	
	(0.253)	(0.274)	(0.195)		(0.175)	
Ω'_{RD}				1.243***		0.481**
				(0.170)		(0.190)
Ω'_{DR}				0.259		0.104
				(0.195)		(0.155)
I_D			0.432***	1.501***		
			(0.100)	(0.179)		
I_R					0.090	0.176
					(0.097)	(0.166)
R^2	0.73	0.72	0.10	0.11	0.13	0.13
N	9032	9032	9032	9032	9032	9032

Notes: Fixed effect linear models with bootstrapped standard errors in parentheses under the coefficient. Each column heading indicates, in brackets, the equation being estimated and below that, italicized, whether the left-hand side transfer variable is reported by R or D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N=9032.

Table 14: Table 9 using consumption purged of transfers

Equation No.	**(17)**	**(17)**	**(18)**	**(19)**	**(18)**	**(19)**
Transfer report	*R*	*D*	*R*	*R*	*D*	*D*
Ω_{RD}	0.075***	0.090***	0.082***		0.057***	
	(0.029)	(0.030)	(0.020)		(0.020)	
Ω_{DR}	0.036	0.011	0.033		0.025	
	(0.028)	(0.030)	(0.021)		(0.019)	
Ω'_{RD}				0.120***		0.056***
				(0.018)		(0.020)
Ω'_{DR}				0.032		-0.002
				(0.021)		(0.017)
I_D			0.041***	0.144***		
			(0.011)	(0.019)		
I_R					0.000	-0.002
					(0.010)	(0.018)
R^2	0.72	0.72	0.09	0.10	0.11	0.11
N	9032	9032	9032	9032	9032	9032

Notes: Fixed effect linear models with bootstrapped standard errors in parentheses under the coefficient. Each column heading indicates, in brackets, the equation being estimated and below that, italicized, whether the left-hand side transfer variable is reported by R or D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N=9032.

Table 15: Table 9 including dyads living in same location

Equation No.	**(17)**	**(17)**	**(18)**	**(19)**	**(18)**	**(19)**
Transfer report	R	D	R	R	D	D
Ω_{RD}	0.075**	0.090***	0.081***		0.056***	
	(0.030)	(0.029)	(0.020)		(0.020)	
Ω_{DR}	0.036	0.011	0.033		0.026	
	(0.028)	(0.029)	(0.021)		(0.018)	
Ω'_{RD}				0.118***		0.056***
				(0.018)		(0.020)
Ω'_{DR}				0.032		0.012
				(0.021)		(0.017)
I_D			0.040***	0.141***		
			(0.011)	(0.019)		
I_R					0.007	0.017
					(0.010)	(0.017)
R^2	0.72	0.72	0.09	0.10	0.11	0.11
N	13808	13808	13808	13808	13808	13808

Notes: Fixed effect linear models with bootstrapped standard errors in parentheses under the coefficient. Each column heading indicates, in brackets, the equation being estimated and below that, italicized, whether the left-hand side transfer variable is reported by R or D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N=13808.

Table 16: Discrete Choice Models, Partial correlations with transfers: Ω and income

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Transfer report	*R*	*D*	*R*	*D*	*R*	*D*	*R*	*D*
Ω_{RD}	0.598***	0.304	0.367***	0.242**				
	(3.23)	(1.64)	(4.28)	(2.42)				
Ω_{DR}	0.284	0.235	0.146	0.128				
	(1.45)	(1.32)	(1.53)	(1.41)				
Ω'_{RD}					0.928***	0.296	0.560***	0.237**
					(5.15)	(1.60)	(6.88)	(2.37)
Ω'_{DR}					0.303	0.060	0.144	0.039
					(1.53)	(0.39)	(1.50)	(0.46)
I_D	0.303***		0.194***	0.428***	1.095***		0.674***	0.676***
	(3.10)		(3.85)	(6.94)	(6.20)		(7.74)	(5.36)
I_R		0.022	0.082	0.017		0.073	0.005	0.049
		(0.19)	(1.45)	(0.32)		(0.46)	(0.04)	(0.54)
N	4197	3664	9032	9032	4197	3664	9032	9032

Notes: Discrete Choice Models with t values in parentheses under the coefficient. Estimated coefficients are shown * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 (2) presents results from Recipient (Donor) Fixed Effect Conditional Logit. Column 3 (4) presents results from a modified Donor (Recipient) Random Effect Probit model. Columns 5 to 8 replicate these methods using Ω' measures instead of Ω measures the results show that the higher the over-perception of income of donor the higher the transfers. Note that the very weak level of significance of Ω_{RD} in the regressions based on donor reports with Donor Fixed Effect (columns 2 and 6) may be explained by the particularly low number of observations contributing to the identification of the partial correlation.[20]

However, fixed effect (FE) type methods suffer from substantial efficiency losses as compared to methods based on the random effect (RE) principle and suffer from inconsistency biases if there are measurement errors. The latter may be of concern regarding our main variables of interest Ω, Ω', I_R and I_D.[21] Moreover, the double fixed effect approach provides no estimates for the donor and recipient incomes, which are important to distinguish the predictions of our theoretical models summarized in Table 8. Finally, they do not lend themselves easily to estimate discrete choice models. For all these reasons, one may be concerned about the precise identification of the main effects of interest $\beta_1, \beta_2, \beta_3$ and β_4 using FE-based methods displayed in equations (17) to (19).

To tackle these issues we estimated a Modified Random Effect model in line with Hajivassiliou (2012), which extends the Mundlak-Chamberlain approach by characterizing the correlations between the unobserved persistent heterogeneities α_i ($i = R$ in equation (18) or $i = D$ in equation (19)), and regressors as follows:

$$E(\alpha_i|\Omega_{RD}, \Omega_{DR}, \mathbf{P}_{RD}, I_D, I_R, \mathbf{Z}_D, \mathbf{Z}_R) \quad = \quad \mu_i = g_i(\Omega, P, I, Z)$$

assuming that $g_i(.)$ is a linear function of the regressors, that $g_i(.)$ depends only on the regressor data for individual i and that $g_i(.)$ only depends on the regressors in a household j invariant way.

This method involves simply adding the fixed household i regressors and family network averages of household j varying regressors as additional regressors in the right hand side of the models specified by equation (18) and equation (19) and proceeding with the RE Probit estimator to obtain consistent and efficient estimates. Note that we also nest the Random Effects within the extended family network clusters to account for possible correlations.

Columns (3)-(4) of Table 16 for Ω and columns (7)-(8) for Ω' show that our main results are robust to using a modified RE approach to control for the unobserved heterogeneities that may characterize Recipients or Donors of transfers. As with the FE approach, we find

[20]A usual shortcoming of this approach is that the identification comes only from the switchers, which explains the low number of observations reported at the bottom of the Table.

[21]However, we are less worried about measurement errors concerning the variable Ω than concerning Ω', which is one of the reasons why we may prefer the Ω measure for our results.

significant and positive correlations between transfers and misperceptions of donor's income but no significant correlations with misperceptions of recipient's income, once controlled for both donor and recipient actual incomes. We also find that the income of the donor is positively correlated to the transfers, as expected with a model of pressure to give or exchange with recipient having full bargaining power, and that the income of the receiver is clearly not significantly correlated to the transfers, rejecting the model under altruism or exchange with donor having full bargaining power.