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A gravity model and network analysis of household food sharing in Zambia

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Abstract

Food sharing is an important part of smallholder food systems and can help households to buffer food security shocks. Household food sharing is the smallest scale food exchange system, yet we do not understand how it compares with food exchange networks at other spatial scales. To this end, we collect information on bilateral household food sharing in two villages in Zambia with approximately 50 households each. We observed seasonal fluctuations for the density of the food sharing. To our knowledge, we are the first to show that the gravity model of trade is applicable to household food sharing. Additionally, sharing networks exhibit the same statistical properties as food exchanges in other locations and at different spatial scales. Specifically, maize exchanges (in mass) follow the Gamma distribution and the relationship between household mass flux and connectivity follows a power law distribution. This work sheds light on household food sharing in rainfed agricultural systems and suggests common underlying mechanisms of food exchange systems across spatial scales and geographies.

1. Introduction

Food sharing is an important part of smallholder food systems (Baggio *et al* 2016, Nolin 2010). Household food sharing is the smallest scale food exchange system and can be thought of as micro-scale food trade. Just as food trade is a way for nations to increase their resilience to production shocks, household sharing is an important way for households to spread their production risk. However, we know relatively little about how food sharing between households compares with the exchanges of food at larger spatial scales (e.g. sub-national food supply chains or food trade between nations), largely due to lack of available household sharing data. To this end, we collect information on household sharing for two villages in Zambia and then evaluate how well statistical models of food trade describe food sharing. Specifically, we quantify the social network statistics of food sharing and compare them with food exchange systems in other locations and at different spatial scales. We also test whether or not the gravity model of trade explains inter-household sharing.

The gravity model of trade is a well-accepted empirical model to predict international trade flows. The gravity model is based on Newton's law of gravity, in which the value of trade flows between two countries is proportional to their mass, represented by their economic size (measured by GDP) and inversely proportional to the geographic distance between them. It is unclear if the gravity model of trade, developed for trade based on market principles at a large spatial scale (e.g. nations), is relevant for sharing systems that are typically based on reciprocity between households or levels of social capital. Previous information on bilateral household sharing presented in Baggio *et al* (2016) does not include the variables necessary (e.g. household wealth, distance) to test whether this relationship holds. If food flows are at least in part determined by these gravity factors, then it can be useful to incorporate these factors to understand the spatial and social factors underlying these sharing relationships. For example, if an influential household lives further away from other members of the village, and has a large asset base, to determine the effect of its influence on food flows, we would need to control for these other gravitational factors. If the gravity model of trade does capture micro-level sharing between households, then this model could be used to estimate food flows across the full spectrum of spatial scales for which we are lack of empirical exchange data.

The concept of networks has been used to study systems ranging from financial investments to the internet (Garlaschelli *et al* 2005, Barabási and Albert 1999). Networks consist of nodes and links, where the nodes are the agents of interest (households) and the links are the interactions between the nodes (food flows). Networks have various structural and statistical properties that give insight into the behavior of the network and can be used to highlight points of weakness or strength. The intensity of the links between nodes can highlight key agents. Recently, network statistics have been applied to household sharing within Alaska (Baggio *et al* 2016) and regional livestock trade in West Africa (Valerio *et al* 2020), helping to determine the critical actors in these systems. Households in Alaska rely on hunting sea mammals, the dominant food item shared. It is unclear if the network properties of these communities will be similar to those of smallholder rainfed systems. If the network properties are similar for villages in rural Zambia, it is suggestive that these patterns may explain sharing networks more broadly.

The focus of this study is the country of Zambia in Sub-Saharan Africa. Zambia is one of the most food insecure nations in the world (FAO 2018), and food insecurity has been growing over the past two decades. Seventy percent of the Zambian population relies on rainfed agriculture (Kanyanga *et al* 2013). During the span of 2014 to 2016, 47.8 percent of Zambians were undernourished, one of the highest levels in Sub-Saharan Africa (FAO 2018). Small-scale farmers reliant on rainfed farming systems produce a majority of food in Zambia and over the last 50 years precipitation has become more variable and the growing season shorter. Intra- and inter-seasonal climate variability have contributed to frequent drought (Sheffield *et al* 2012). Maize is the predominant cereal crop in Zambia and comprises a majority of caloric intake (FAO 2009). Yet maize harvests are anticipated to decrease in Zambia under the threat of climate change (Ringler *et al* 2017). This context poses particular challenges for farmers with small land holdings who may have insufficient harvests to meet household food demand in drought years (Vermeulen *et al* 2012).

Food flows exhibit the same statistical distribution of node connectivity and mass flux from village to global scales in the context of United States (Konar *et al* 2018). We test whether these statistical network characteristics (that have been shown to characterize food sharing in Alaskan villages) hold for villages in the very different agro-ecological and cultural context of Zambia. Additionally, we test the gravity model of trade on food sharing data among village households in Zambia. To do this, we estimate a needs-driven version of the gravity model. To our understanding, this is the first application of the gravity model of trade to household sharing.

2. Methods

Figure 1 provides a map of Zambia, our study location. Zambia has four agricultural seasons: post-harvest (August, September, October), planting season (November, December, January), rainy/growing season (February, March, April), and dry season (May, June, July). Part of the rainy season is known as the hunger or lean season, when smallholder farmers are the most food insecure as food from the previous harvest is expended as the subsequent harvest approaches. Harvest occurs in May/June as rains subside and dry season commences. The southern part of the country experiences the most variability in inter-annual rainfall (Thurlow *et al* 2012) and is the location of our study (refer to figure 1).

2.1. Household sharing survey

We define sharing as the exchange of goods or services between two households. Sharing may be voluntary or may occur for payment (either a cash transaction or payment in-kind through labor or other commodities). Household sharing was captured through a household-level survey instrument. The survey instrument consisted of 14 categories of questions (see table 1) and aimed to capture the majority of bilateral household exchanges in two villages in Zambia. The survey was conducted in the summer of 2018 and asked about sharing that occurred between June 2017 and 2018.

We collected information on five categories of sharing: food, maize, livestock, non-food, and labor (table 2). Note that we break maize out of the broader food category and collect additional information on its sharing intensity (e.g. maize mass flux), since maize is critical for food security in the region and is responsible for the vast majority of calories consumed among rural households (Chapoto *et al* 2010). This means that maize is the only item for which we have information about the quantity exchanged between households. Non-food sharing includes the sharing of electronic devices, modes of transportation, agricultural equipment, fuel, and money. Labor includes

Figure 1. Map of Zambia relative to the continent of Africa. The study area of interest (Zambia's southern province) is shaded.

Table 1. Specific sharing items in each sharing category.

No	Sharing Category	Specific examples
1	Food	Any mealie meal, bread, millet, sorghum, maize, rice, wheat (staples); Irish potatoes, cassava, sweet potatoes,or any other foods made from roots or tubers; vegetables; fruits; any meat, any beef, pork, lamb, goat, chicken, duck, or other birds; fresh or dried fish or shellfish; eggs; beans, peas, lentils, or nuts; cheese, yogurt, milk or other milk products; oil, fat, or butter; sugar or honey; any other foods such as condiments, coffee, or tea
2	Maize	Amount of maize [kg]
3	Livestock	Oxen, breeding bull, donkey, female cattle, goats and/or sheep,poultry, pigs
4	Non-food	Electronic device (radio, television, mobile phone); bicycle, motorcycle, or vehicle; agricultural equipment (water pump/treadles, ploughs, sprayers, ox carts); agricultural supplies (fertilizer, seed, trees, seedlings, herbicide, pesticide); fuel (firewood, charcoal); money; other
5	Labor	Weeding, planting, harvesting, shelling, tilling/soil prep, applying fertilizer, applying herbicides/pesticides, transportation of crops to market, housing or other equipment repair (ex: roofing repair, vehicle repair); other

agriculture-related tasks, transportation to market, and housing and equipment repair. In this way, we collect comprehensive information on the full sharing system.

We obtained the village registries for two villages prior to implementing the survey. We selected the villages such that they were comparable in the number of households. Village 1 is approximately 9 km from a tarmac road and an on-tarmac market with structures. Village 2 is approximately 1.5 km from an off-tarmac market with structures and 22 km from a tarmac road. Village 1 consists of 47 registered households, 37 of which were surveyed (78.7 percent). Village 2 consists of 56 registered households, 47 of which were surveyed (84 percent). We constructed sharing networks between 47 households in Village 1 and between 58 households in Village 2 via direct and indirect households reporting. Two households in Village 2 were not part of the village registry and were not surveyed but are included in the sharing network construction because they were referenced more than once by different households. Those who owned land in the village but did not regularly reside in the village, those who were too ill to complete the survey, or those who were absent from the village during the survey period were not surveyed. The average survey took approximately 1 hour to conduct and was implemented by enumerators who spoke the local language.

2.2. Network statistics of household sharing

We calculate directed/undirected matrices of maize, livestock, non-food and labor flows, as well as

Table 2. Overview of survey implemented in both villages for each household.

No	Survey section	Specific examples
1	General household information	Household's latitude and longitude, village, camp, name of head of household
2	Establish participation in sharing	Selection of households shared with in past year
3	Instances of supplying	Instances of household supplying food, maize, livestock, non-food, labor; season supplied most; reason for supplying
4	Instances of receiving	Instances of household receiving food, maize, livestock, non-food, labor; season received most; reason for receiving
5	Relationships between interacting households	Family relative (by blood or marriage),family friend, village elder, other
6	Household size and structure	Travel time by foot to various locations (i.e. tarmac road, market), household's compound structure (i.e. number of structures for sleeping, cooking)
7	Household demographics	Household members relationship to head of household, sex, year of birth, educational attainment, whether has lived at household since birth
8	Assets and income	Count of various assets (i.e. number of mobile phones, bicycles, livestock), breakdown of annual income, breakdown of annual expenses
9	Dietary diversity and expenses	Number of days consumed various foods, source of food, use of coping mechanisms
10	Agricultural land	Amount of farmland and arable land
11	Maize production	Amount of maize planted, harvested, and stored
12	Production diversity	Number of items produced,grown, gathered, or caught by household
13	Rainfall	Rainfall characterization
14	Invasive species	Potential agricultural damage to due pests

weighted/unweighted matrices of maize. We constructed the directed networks for each of the 5 sharing categories as we collected both donor and recipient information. We captured seasonal data and aggregated it to construct the networks at the annual time scale.

The directed networks for food, livestock, non-food, and labor sharing are captured as binary interactions. Each element (a_{ij}) in the matrix indicates whether an exchange between nodes i and j occurred: a sharing interaction between nodes i and j is indicated by a one, whereas no sharing interaction between nodes i and j is indicated by a zero. When direction is not considered, the adjacency matrix is symmetric and referred to as an undirected matrix. In an undirected matrix, each element a_{ij} equals one when a connection exists between node i and j and zero when it does not. Node degree (k) indicates the nodes number of unique links. For a directed matrix, there are two degree types: in-degree (k_{in}) and out-degree (k_{out}). k_{in} is the summation of incoming links ($k_i^{in} = \sum_j a_{j,i}^{in}$). k_{out} is the summation of outgoing links ($k_i^{out} = \sum_j a_{i,j}^{out}$). The total degree is $k_i^{total} = k_i^{in} + k_i^{out}$ (Costa *et al* 2007) and indicates the total number of households shared with for each node. For example, if household i supplies food to three households, and receives from one household, then its out-degree is 3, its in-degree is 1, and its total degree is 4. For undirected matrices, in-degree and out-degree are equivalent.

Network density is the number of existing links divided by the potential number of links and is calculated by $p = M/[N(N-1)]$, where N is the number of nodes, M is the number of links and $N(N-1)$ is the number of potential links (Costa *et al* 2007). Centrality (C) is an important indicator for identifying the important nodes within network. There are four well-known centrality measures: degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality—each with its own strengths and weaknesses. We do not calculate closeness centrality because our graphs are unconnected (Costa *et al* 2007, Bonacich 2007, Rochat 2009). Degree centrality (C_D) is the simplest centrality measure, defined as the links associated with each node, divided into in-degree centrality, out-degree centrality, and total degree centrality. Betweenness centrality (C_B) of node u is the summation over all pairs of nodes i and j of the number of shortest paths between nodes i and j that pass through node u divided by the total number of shortest paths between i and j; $C_B = \sum_{i,j} \sigma(i,u,j)/\sigma(i,j)$ (Costa *et al* 2007). Eigenvector centrality (C_E) are achieved by assigning relative scores to all nodes in the network under the assumption that connections with higher scoring nodes contribute more than connections with lower scoring nodes. C can be normalized by dividing the sum of centrality scores for all nodes so it is between 0 and 1.

Maize is the only sharing category that captures mass. The mass of maize exchanged between two households is denoted as a weight (w_i), resulting in a weighted, directed network. If no maize was exchanged the weight is zero. The node strength is determined by summing all node weights: strength-in ($s_i^{in} = \sum_j w_{j,i}^{in}$), strength-out ($s_i^{out} = \sum_j w_{i,j}^{out}$), and total strength ($s_i^{total} = s_i^{in} + s_i^{out}$). For example, if household i supplies three households each with 10 kg of maize, and receives 5 kg of maize from one household, then its out-strength is 30 kg, its in-strength is 5 kg, and its total strength is 35 kg. For a weighted, undirected network, strength-in (s_i^{in}) and strength-out (s_i^{out}) are equivalent and the matrix is symmetric (Costa *et al* 2007).

The network properties provide insight into the flow strength between nodes. In previous work, the Poisson process was used to model food flows between nodes in the United States, with a constant success rate, $\frac{1}{\theta}$ (Lin *et al* 2019). For any two nodes in the sharing network, i and j, the quantity of the shared commodity can be estimated as a function of the explanatory variables, $k(X_{ij})$. For each shared commodity unit, there is a constant success rate, $\frac{1}{\theta}$, determining the success or failure of the sharing relationship. Gamma distribution is a discrete probability distribution for the number of successes in a sequence of independent and identically Poisson process. With Poisson process assumption, we come to the conclusion:

$$P(flow_{ij}|X_{ij}) = Gamma(k(X_{ij}), \theta) \quad (1)$$

Considering the scaling property and summation property of Gamma distribution, the commodity flow across the whole network following a Gamma distribution is a necessary but insufficient condition for the assumption that the commodity sharing between any two households is a Poisson process; detailed mathematical derivation is shown in the SI S1.4.2. If $flow_{ij}$ for the network follows a Gamma distribution, then the Poisson process can be used to model household sharing.

2.3. Gravity model of trade at household scale

We implemented the gravity model with the hypothesis that household sharing is influenced by the same factors that affect international trade. We fit a gravity model regression that accounts for link intensity for maize flows and a logit gravity model regression for all other commodities (since we only have data on sharing intensity for maize). We scaled the variables to be representative of the household scale; see table 3 and equation (2). The presence or absence of the commodity sharing between each household pair is indicated by the binary outcome 1 or 0. The value of maize (in Kwacha) shared from household i to household j is the trade flow in this application of the gravity model. The value of maize is the average monthly maize price per bag for the survey time period divided by the standard maize bag size (50 kg), resulting in an approximate price of 0.73 Kwacha per kilogram (Zambia Data Portal: Central Statistical Office 2016). This approximate price per kilogram is then multiplied by the mass of maize exchanged between household i and household j to equal the value of maize exchanged between the households. We measure economic size as the annual income of the household (in Kwacha). Distance is the geographic distance between interacting households (in meters).

The data set comprises both Village 1 and Village 2, resulting in a sample size of 81 households: 37 households in Village 1 and 44 households in Village 2. Note that 3 households were excluded from the 47 surveyed households in Village 2 because of incorrect GPS coordinates.

The simple form of the gravity model at the household level is:

$$\log M_{ij} = c + b_1 \log inc_i + b_2 \log inc_j + b_3 \log distance_{ij} + e_{ij} \quad (2)$$

M_{ij} is the value of maize exchanged from one household to another (Kwacha), inc_i is the annual income of household i (Kwacha), inc_j is annual income of household j (Kwacha), $distance_{ij}$ is the geographic distance between household i and household j (meters), c is the constant of the regression, the b terms are the estimated coefficients, and e_{ij} is an error term.

We followed the methodology in 'The Gravity Model of International Trade: A User Guide' (Shepherd 2016). The first step in determining if the gravity model of trade is applicable is to see if there are correlations present in the basic gravity model. The initial correlation helps establish relationships between the variables, or the lack thereof. Following Shepherd (2016), we implement the Poisson Pseudo-Maximum Likelihood Estimator, proposed by Silva and Tenreyro (2006), because the OLS regression model has limitations with trade data. The first potential problem is the chance of the error term being heteroskedastic, violating the first assumption of the OLS regression model. The second problem is related to the prevalence of zeroes in trade data. The bilateral trade matrix for aggregate international trade data is half filled with zeroes (Helpman *et al* 2008). This is also true for household sharing data. Values of zero are excluded in the OLS regression model since the logarithm of each variable is taken which reduces the sample size and can lead to sample selection bias. The Poisson Pseudo-Maximum Likelihood Estimator, allows for the inclusion of zero values as it does not take the logarithm of the trade value.

Beyond its simplest form, gravity models of trade often include other measures of trade frictions, such as common land border and official language (Anderson and Wincoop 2003, Rose 2004). These indicator variables can be added to the regression model as explanatory variables. Analogous variables exist for the household scale (table 4). Our data only capture sharing that exists within each village, thus common village between exchanging households is not a usable dummy variable as it would result in multicollinearity. Similarly, common language is not a usable dummy variable as the villages both speak the local language of the province. The distinction of whether the exchange occurred in Village 1 or Village 2 is a fixed effect variable as each village has unique properties that could impact exchanges. We did not have

Table 3. Variables used in gravity model for international trade versus variables used in gravity model for household sharing.

International Trade		Household Sharing	
Variable	Description	Variable	Description
X_{ij}	Exports from country i to country j	M_{ij}	Trade value of maize supplied from household i to household j
GDP_i	GDP of country i	inc_i	Annual income of household i
GDP_j	GDP of country j	inc_j	Annual income of household j
$distance_{ij}$	Geographical distance between countries	$distance_{ij}$	Geographical distance between households

complete kinship data for the villages. As a proxy, we use shared names to indicate whether the exchanging households are related; though, we acknowledge that shared names do not necessarily connote familial relationships.

We added additional variables to the regression models to act as friction factors. These are variables that would potentially impact the desire or likelihood that a household shares maize. We use the travel time (walking) from households to village market as friction factor variables. Variables pertinent to maize sharing and not directly analogous to the gravity model of trade at the international scale are also added to capture other supply and demand factors. Whether or not the donor households had maize storage from the 2016/2017 season, the amount of land cultivated by households in the 2017/2018 season (as it is presumed this amount would not have drastically changed between the 2016/2017 and 2017/2018 seasons), and the food consumption scores of the donor and recipient households are added as additional explanatory variables relative to the context of maize sharing (United Nations World Food Programme 2008).

A logit gravity model was applied to the unweighted directed network of all categories. Logistic regression allows us to establish a relationship between a binary outcome variable and a group of predictor variables. Here we use Y to represent the binary outcome variable indicating the existence or not of the food/labor/nonfood/maize/livestock link with $\{0,1\}$, where p is the probability that $y = 1$; $p = P(y = 1)$; this is a gravity model of the occurrence of commodity sharing. When two households are close, the probability that these two households share is greater. When the economic size of the households is large, they are also more likely to share. The effect of additional variables in the gravity model was also examined. The predictor variables included distance between donor and recipient (*distance*), donor income ($income_i$), recipient income ($income_j$), household location (*village*), binary indicator of familial relationship between donor and recipient (*related*), donor maize land area ($land_i$), recipient maize land area ($land_j$), donor maize storage ($storage_i$), recipient maize storage ($storage_j$), donor total farmland ($farmland_i$), and recipient total farmland ($farmland_j$), represented by $x_1,\ldots,x_k$. Then the logistic regression of Y on $x_1,\ldots,x_k$ estimates parameters values for $\beta_0,\beta_1,\ldots,\beta_k$ via the maximum likelihood method as:

$$logit(p) = \log(p/(1-p)) = \beta_0 + \beta_1 \times x_1 + \beta_2 \times x_2 + \ldots + \beta_k \times x_k \quad (3)$$

Network statistics consider the interaction between the nodes and the importance of each node in the whole network. Gravity model fitting shows the impact of environmental variables on the exchange occurrence and flow strength. Then, the question of whether the commodity exchange of one household will be impacted by the neighboring households sharing situation naturally arises. We employed the Poisson regressions with household-specific non-spatial effects and neighbourhood based household-specific spatial effects. The idea of spatial autocorrelation (SAR) was inspired by Whittle (1954), who defined a family of linear spatial process models, in which an endogenous variable is designated as dependent on the spatial interactions between cross-sectional elements and a disturbance term, accoding to the following equation:

$$Z = \rho WZ + X\beta + \varepsilon \quad (4)$$

where Z refers to the household-specific total maize flow , ρ is an autoregressive parameter; W represents a pre-defined weights matrix used to specify the relationship between each household; X is a set of exogenous variables including household income, location, maize land area, maize storage, farmland area, time to market, and food security score. β is a vector of parameters that describe the effects of X on Z. ε, a vector of disturbances. If $(I-\rho A)$ is invertible, we can deduct the 'reduced-form' spatial autocorrelation model as:

$$Z = A^{-1}X\beta + A^{-1}\varepsilon \quad (5)$$

where $A = I - \rho W$ and I is an identity matrix. We constructed the pre-defined weights matrix, W, using a row-standardized inverse distance matrix, utilizing the Euclidean distance between the three nearest neighbors. To estimate the autocorrelation ratio, ρ, and parameters, β, we applied an aspatial maximum

Table 4. Units of variables used in gravity model for household sharing.

Variable	Variable label
M_{ij}	Trade value of maize supplied from household *i* to household *j* [Kwacha]
inc_i	Annual income of household *i* [Kwacha/year]
inc_j	Annual income of household *j* [Kwacha/year]
$distance_{ij}$	Geographical distance between households [kilometers]
village	1 if household *i* and household *j* belong to Village 1, 0 otherwise
related	1 if household *i* and household *j* share a common name, 0 otherwise
$market_i$	Travel time on foot from household *i* to village market [hours]
$market_j$	Travel time on foot from household *j* to village market [hours]
$storage_i$	1 if household *i* had maize in storage from the 2016/2017 harvest before the 2017/2018 harvest, 0 otherwise
$storage_j$	1 if household *j* had maize in storage from the 2016/2017 harvest before the 2017/2018 harvest, 0 otherwise
$land_i$	Household *i*'s total size of land cultivated with maize in the 2017-2018 growing season [hectares]
$land_j$	Household *j*'s total size of land cultivated with maize in the 2017-2018 growing season [hectares]
FCS_i	Food consumption score of household *i*
FCS_j	Food consumption score of household *j*

likelihood based Poisson estimator (aspatial Poisson ML) and full information maximum likelihood based Poisson estimator following Lambert *et al* (2010).

3. Results

3.1. Village scale summary statistics

Both villages have similar mean household sizes, primarily male head of households, and household inhabitants are over 50 percent female (refer to table 5). The average household head age is younger in Village 1 than in Village 2. The villages access to a tarmac road, market, and transportation vary. Village 2 reports greater travel times to a tarmac road compared to Village 1. Most households in both villages report visiting one market.

Village 1 has a higher average food consumption score than Village 2, approximately 54 and 44 respectively, where greater than 35 is considered 'Acceptable'[5]. There is more variability in food consumption scores in Village 2. Approximately 80 percent of households in Village 1 have food consumption scores in the 'Acceptable' range compared to approximately 65 percent in Village 2. No households in Village 1 have food consumption scores in the 'Poor' range, and less than 10 percent of Village 2 is profiled as 'Poor'.

The vast majority (83.0 percent) of the households in Village 1 participated in non-food sharing at least once during the year, followed by food sharing (78.7 percent) and labor sharing (78.7 percent). A majority (79.3 percent) of the households in Village 2 participated in food sharing followed by non-food sharing (70.7 percent) and labor sharing (70.7 percent). In both villages, households participated least in livestock sharing. More households in Village 1 participated in maize sharing at least once during the year compared to Village 2: 66.0 percent of households in Village 1 compared to 48.3 percent of households in Village 2. Of the maize sharing interactions that occurred, the average mass of maize exchange was greater in Village 1 than that in Village 2.

3.2. Village network statistics

3.2.1. Density

Many households participate in multiple types of sharing (figure 2). The annual sharing networks for Village 1 have greater densities in every category than those of Village 2. Annual food sharing is the densest sharing category for both villages (table 6). Village 1 has an annual food sharing network density of 0.041. Village 2 has an annual food sharing network density of 0.033. In Village 1, the network density of annual livestock sharing is the lowest. In Village 2, the network density of annual maize sharing is the lowest.

The density of sharing in all sharing categories fluctuates across seasons (figure 3). With regard to food sharing, households share with some households exclusively during one season whereas some households will share with other households during multiple seasons. The greatest food network densities occur during different seasons between the two villages: Village 1 has the greatest network density during the rainy season and Village 2 has the greatest network density during dry season. The greatest network densities for maize and livestock sharing occur during the planting season in both villages. The smallest network densities for non-food, labor, and livestock sharing occur during the post-harvest season in both villages. Both villages saw more instances of labor sharing during the dry season: the greatest density during the dry season in Village 2 and equally large densities during dry and planting season in Village 1. The seasonal network densities of labor sharing follow the same trend for both villages: at the lowest density during post-harvest season, greater during

[5]There are three food security profiles associated with the FCS. A FCS between 0 and 21 is considered Poor, a score between 21.5 and 35 is classified as Borderline, and a score greater than 35 indicates Acceptable food security (United Nations World Food Programme 2008).

Table 5. Summary statistics for various village properties.

	Village 1	Village 2
Food Consumption Score	54	44
Household size	6.3 ± 3.1	6.9 ± 3.4
Household heads age	36.8 ± 13.0	44.4 ± 15.8
Percent of male head of household	86.5	89.4
Percent of household that is female	56.0	54.0
Travel time to tarmac (minutes)	134 ± 93.0[a]	259.2 ± 49.4[b]
Travel time to transportation (minutes)	134 ± 93.0[a]	18.0 ± 9.9
Travel time to market (minutes)	61.7 ± 46.8	18.0 ± 9.9
Travel time to water (minutes)	6.8 ± 7.7	3.7 ± 2.8
Travel time to firewood source (minutes)	16.1 ± 17.3	114.5 ± 71.3[c]
Travel time to primary maize field (minutes)	7.3 ± 14.39146	27.9 ± 41.4
Number of markets visited in last month	1.2	1.1

[a] 2 households indicated it was too far to walk and were excluded from the mean/standard deviation calculation. 35 households were included in the mean/standard deviation calculation.
[b] 35 households indicated it was too far to walk and were excluded from the mean/standard deviation calculation. 12 households were included in the mean/standard deviation calculation.
[c] 15 households indicated it was too far to walk and were excluded from the mean/standard deviation calculation. 32 households were included in the mean/standard deviation calculation.

Table 6. Annual network parameters for directed networks.

		Village 1	Village 2
Food	# of Active Nodes[a]	37	46
	# of Links	89	109
	Density	0.04 117	0.03 297
Maize	# of Active Nodes	31	28
	# of Links	37	24
	Density	0.01 711	0.00 726
	Total Mass [kg]	3470	1819
	Average Mass [kg][b]	93.8	75.8
	Standard deviation Mass [kg][c]	111.5	131.5
Livestock	# of Active Nodes	26	27
	# of Links	25	28
	Density	0.01 156	0.00 847
Non-Food	# of Active Nodes	39	41
	# of Links	84	62
	Density	0.03 885	0.01 875
Labor	# of Active Nodes	37	41
	# of Links	61	79
	Density	0.02 821	0.0239

[a] Active nodes represent the households participating in the sharing.
[b] Average maize shared among participating households.
[c] Standard deviation of maize shared among participating households.

planting and dry season, and low during the rainy season.

Households exchange various masses of maize (figure 4). The annual maize sharing network of Village 1 has a greater density than that of Village 2, 0.017 and 0.007 respectively. Village 1 exchanged more maize in total than Village 2, 3470 kg versus 1819 kg. Village 1 exchanged the largest quantity of maize during the dry season (1530 kg). Village 1 did not exchange the greatest quantity of maize during the same season its greatest network density occurred. Village 1 exchanged the most mass during the dry season but the planting season had the greatest network density. Village 2 exchanged the largest quantity of maize during the planting season in (875 kg). Village 2 exchanged the greatest mass during the planting season which is also the season with the greatest network density.

3.2.2. Centrality

The mean centrality and degree for annual food sharing is similar for Village 1 and Village 2 as shown in figures 5(a) and (b). For different centrality measures, similar important nodes are identified. The correlation coefficients between any two centrality measures are shown in figures 5(e) and (f). Village 1 exchanges more maize mass on average than Village 2. The betweenness centrality and degree distributions for the annual food networks demonstrate similar properties to those presented in the literature (Konar et al

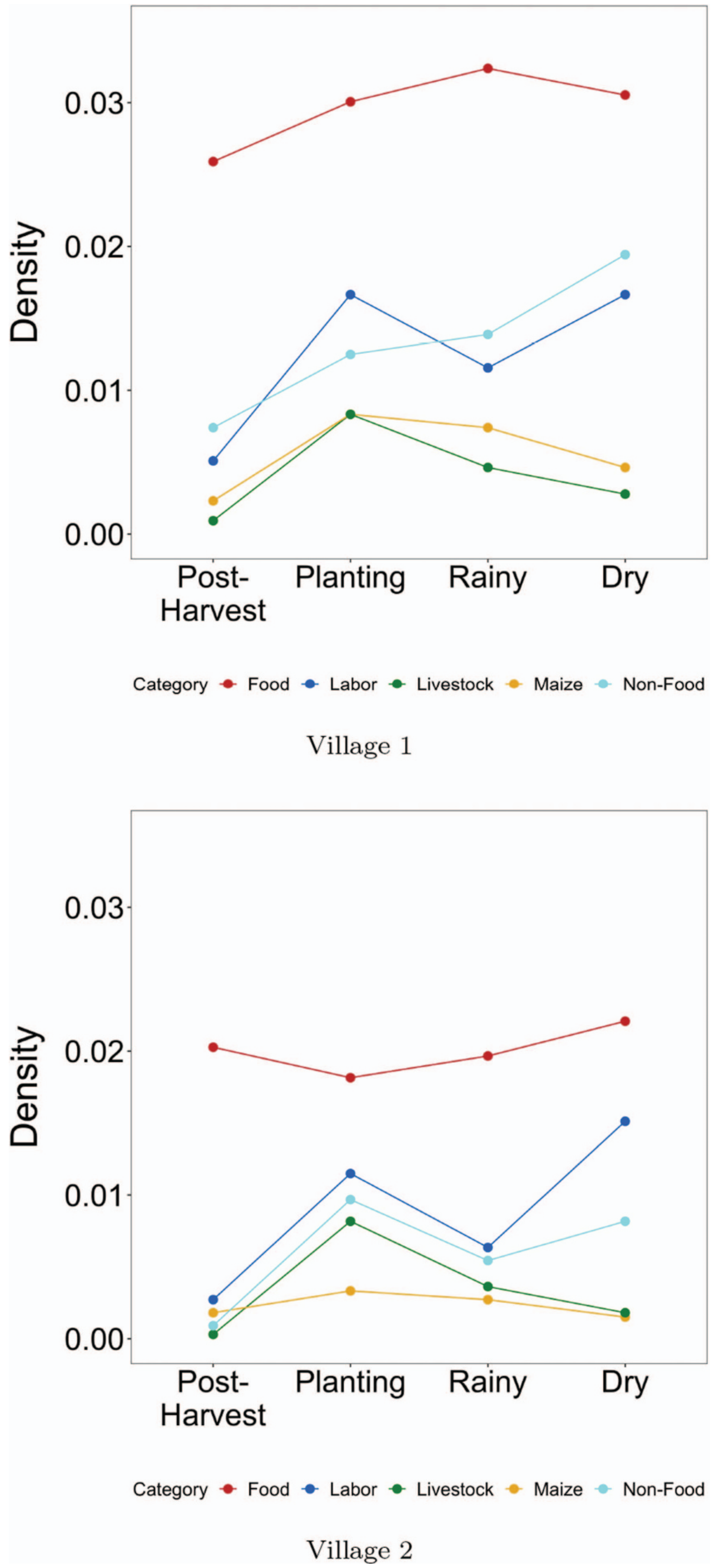

Figure 2. Comparison of Village 1 and 2 network densities for seasonal sharing. Density is not constant across growing seasons; there are seasonal fluctuations in every sharing category. The food and maize categories do not fluctuate as much as labor, livestock and non-food for Village 2.

2018, Baggio *et al* 2016). The mean betweenness centrality was approximately 0.02 for the villages, which is similar in magnitude to the betweenness centrality of sharing in Alaskan villages (Baggio *et al* 2016). Village 1 and Village 2 had a mean degree of approximately 5, which is smaller than that of the Alaskan villages but within similar magnitudes. The average undirected strength [kg] (see figure 5) was significantly less

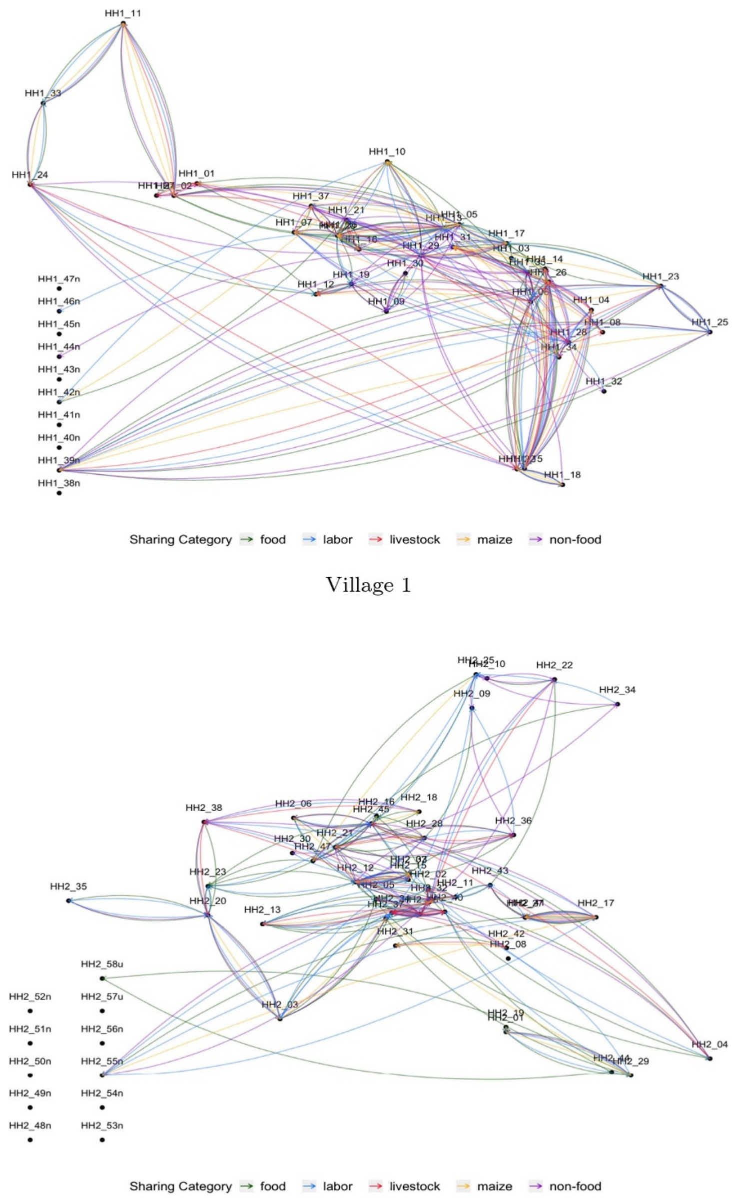

Figure 3. Annual sharing networks for all categories. Households that were not surveyed are indicated by a 'n' or 'u'. The distance between households in the figure is an equal scale of the actual distances between households, but individual household locations are no longer accurate with respect to latitude/longitude coordinates. Households appear to participate in multiple sharing categories.

in Village 1 and Village 2 compared to the strength of the Alaskan villages; however, the Alaskan villages capture the mass of many types of food flows, such as animal products, whereas our study only captures the mass of maize exchanged.

3.2.3. Degree and strength distribution

The distribution of node strength for food trade was shown to follow a Gamma distribution across scales in Konar *et al* (2018). Konar *et al* (2018) also found that the relationship between node degree and strength of food trade follows a power law across scales. We fitted the Gamma distribution to maize flows. A linear relationship is fitted to log(s) and log(k) such that:

$$\log(s) = a + b\log(k) \tag{6}$$

The maize flux fitting results are shown in figures 6(a) and (b) and table 7. The Kolmogorov–Smirnov test (Massey Jr 1951) results indicate that we cannot reject the null hypothesis that our samples are drawn from the Gamma distribution. A variety of distributions are fit to maize mass flux in the SI and the Gamma distribution fits the data the best. Since maize flows follow the Gamma distribution (see figures 6(c) and (d)) food sharing can be treated as a Poisson process. The relationship between maize strength and maize degree follows a power law distribution (see figure 7 and table 7).

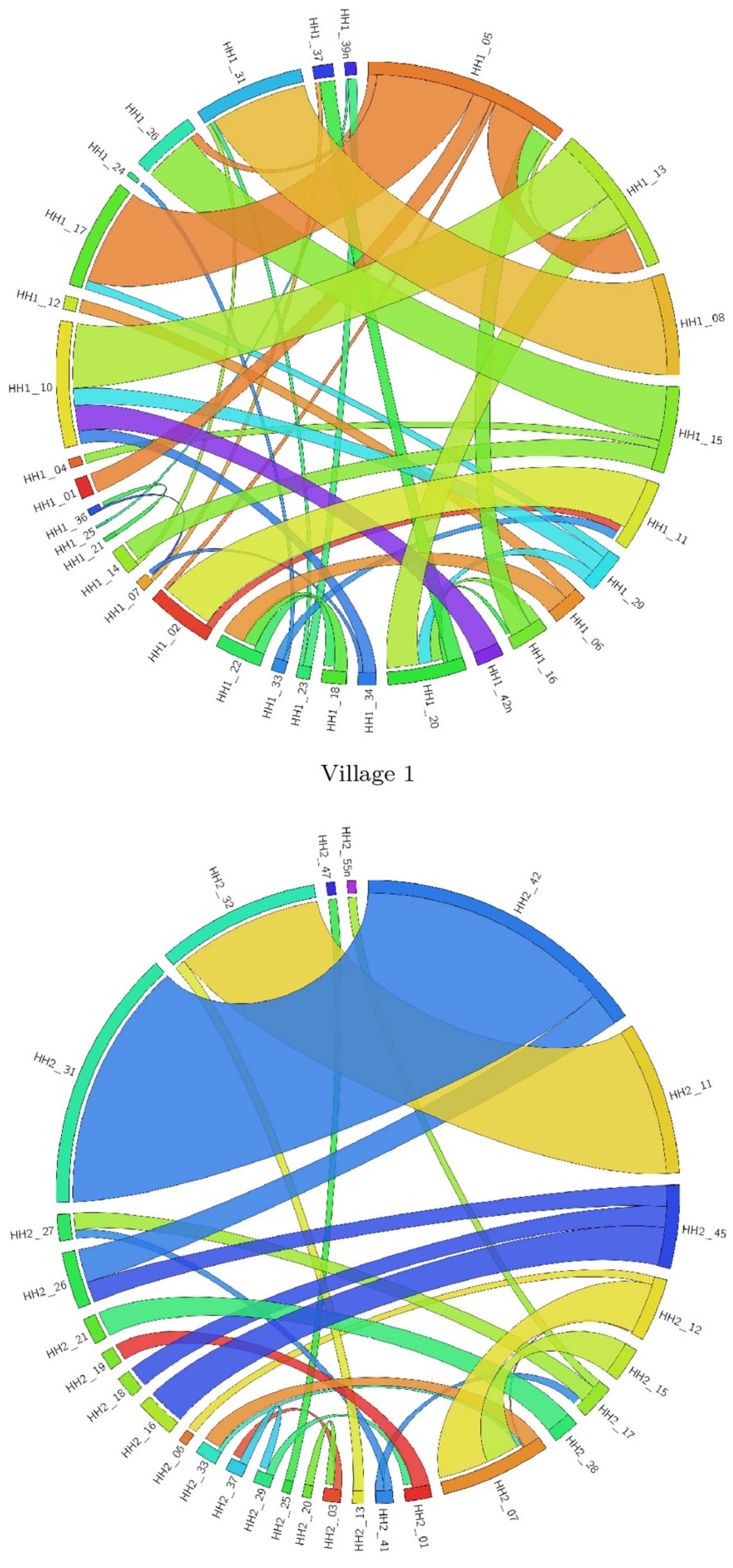

Figure 4. Weighted annual maize sharing networks. Mass of maize exchanged is proportional to the width of the link. Households that were not surveyed are indicated by a 'n' or 'u'. Households exchanged various masses of maize amongst each other.

3.3. Gravity model of trade at the household level

3.3.1. Gravity model

Household level maize exchanges demonstrate relationships predicted by the gravity model of trade using the Poisson Pseudo-Maximum Likelihood Estimator (see table 8). The method considers over 2600 observations in each model, increasing the statistical power of the analysis; however, the R^2 values are low, less than 0.09. The donor households income is statistically significant in almost all models and is

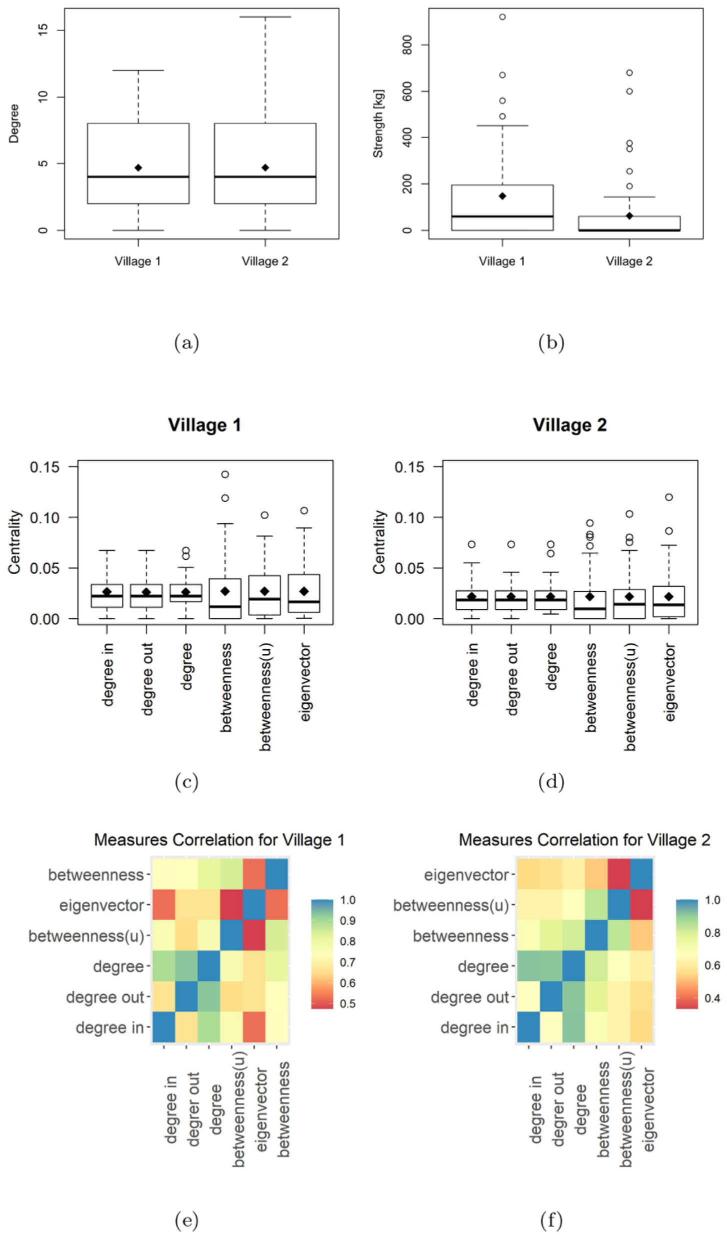

Figure 5. Comparison of centrality scores of village 1 and village 2 annual food networks. Boxplots of (a) Degree of food network. (b) Strength [kg] of maize network. Village 1 and Village 2 demonstrate similar degree distribution; however, more maize mass is exchanged on average in Village 1.(c) Village 1 centrality, (d) Village 2 centrality, (e) Village 1 measures correlation, (f) Village 2 measures correlation.

positive in all models. The coefficients of the recipient households income are (largely) positive, though not statistically significant. Distance is statistically significant in all 7 models, and it is consistently negative[6]. These results are indicative of the traditional gravity model of trade.

Our findings suggest that the gravity model of trade is applicable at the household level using the Poisson Pseudo-Maximum Likelihood (PPML) Estimator to capture a larger sample size. Distance is negatively associated with the value of maize shared; this is consistent with the classic gravity model of trade, as is the positive association between donor household income and the value of maize shared. The categorical variable 'Village', analogous to common border and region variables of international trade models, is significant in all models it is included in. 'Village' is consistently positive, indicating that belonging to Village 1 is positively associated with the value of maize exchanged. This finding is supported by the higher annual maize sharing network density of Village 1 compared to that of Village 2.

[6]The coefficients themselves should be treated with caution in this setting since the cross-sectional nature of our data do not allow us to disentangle the effect of household-specific factors from the multilateral resistance concept in the gravity model of trade, that has been shown to introduce bias.

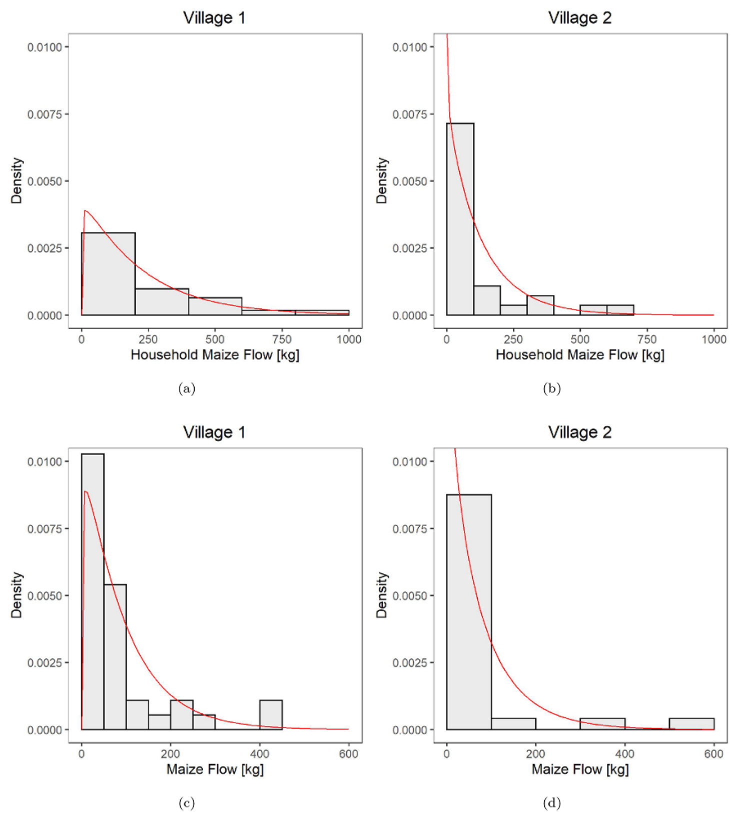

Figure 6. Network distributions for annual maize flows. Gamma distribution is fit to (a), (b) density of maize strength and (c), (d) density of flows. The Gamma distribution fits the data well.

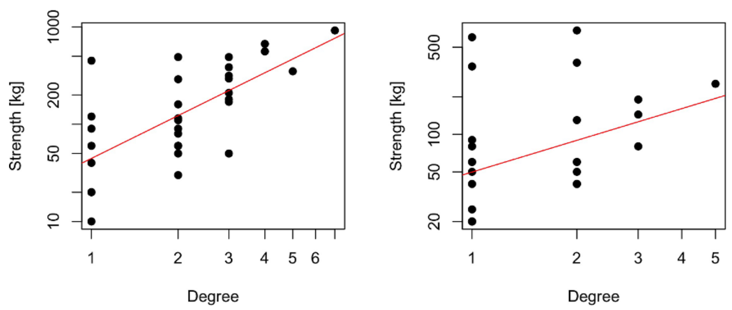

Figure 7. Network distributions for undirected annual maize flows. Power law distribution is fit to strength versus degree.

We also include variables that reflect supply and demand on the part of both households. The presence of maize storage from the 2016/2017 harvest at a recipients household is statistically significant and negative implying that those households with more maize on hand are less likely to receive maize from their family or neighbors. The donor household food consumption scores are positively associated with the value of household maize exchanged and statistically significant. Thus, food secure households were more likely to share maize with others. Other factors, such as the village the exchange occurred in, the presence of maize storage from the past agricultural season of the recipient households, and food consumption score of donor households, are influential in household maize exchanges.

3.3.2. Logit gravity model

The logit gravity model was applied to the binary occurrence data of all commodities as shown in table 9. Regression coefficients, β, and standard errors are provided (as explained by equation (3)). The effect of distance and income is consistent with what the gravity model predicts. The coefficient is negative for distance and positive for donor and recipient income, implying that greater distance and smaller economic size decreases the propensity of exchange. Households are more likely to share when they are not far from each other and at least one of them have high income.

T-statistics indicate that both *village* and *relationship* are important explanatory variables. *Related* is statistically significant and positively associated with

Table 7. Parameters for undirected maize flow networks. Gamma distribution is fit to node strength. Power law is fit to node degree versus strength.

	Village 1	Village 2
Strength Distribution(Gamma)		
α	1.06	0.96
θ	211.73	134.82
ks score	0.11	0.23
Flow Distribution(Gamma)		
α	1.09	0.85
θ	85.74	89.57
ks score	0.16	0.20
Power Law Fit		
a	1.649	1.697
b	1.462	0.845
R^2	0.456	0.145

fluxes, indicating that sharing is more likely to happen between related households. The coefficient on *village* was statistically significant and positive; households in Village 1 are more like to share. This is consistent with the Poisson Pseudo Maximum likelihood Estimator results for maize sharing. Some differences exist. The coefficients in the logit gravity model imply that sharing is more likely to occur between households with plentiful land, high storage, and high food security. The PPML gravity model results shows that the flux weights are related to donor storage, land, and FCS, and inversely related to recipient storage, land, and FCS. Note that we use the log-form of the distance and income in this regression model, as the log form transformation gives a better fitting result according to the Akaike information criterion (AIC scores), implying that the impact of distance and income on the probability decrease as value increases.

3.3.3. Spatial correlation

Table 10 shows the estimation of coefficients, ρ and β, presented in equation (4), using the aspatial Poisson model and the spatial model with Full Information Maximum Likelihood (FIML) Poisson estimator. Compared with its spatial analogues, the aspatial model actually performs quite well. The reason is that our sample size is quite small. The simulation results in Lambert *et al* (2010) show that with the increase of sample size, the spatial estimator is superior to the aspatial estimator in terms of deviation. The autoregressive coefficient ρ is statistically significant and positive, suggesting that maize sharing in neighboring households might stimulate the maize sharing of target households. Households with less maize land and low maize storage but high income and FCS index were more likely to stimulate food sharing. Households in Village 1 were more likely to share maize.

4. Discussion

4.1. Understanding household sharing in Zambia

The greater annual network densities of all categories of sharing for Village 1 could be attributed to a variety of village attributes, such as market access and/or the larger percentages of the village participating in the various categories of household sharing at least once during the year. Village 2's closer proximity to a larger market with structures could decrease the reliance on household food sharing.

Food sharing in Village 1 behaves how we would anticipate: the most food sharing occurs during the rainy season followed by the dry (harvest) season. The latter part of the rainy season is also known as the hunger/lean season; thus, we anticipate more sharing during the rainy season as households are most food insecure prior to harvest. The food sharing network is the least dense during post-harvest in Village 1, which makes sense as the households would have completed all of their harvesting by this time period and are expected to be most food secure during this time. The increase of food sharing during the rainy and dry (harvest) seasons could be associated with the shortage of goods before harvest, aligning with interpretations of similar behavior in other studies (Boafo *et al* 2016). On the contrary, the most food sharing occurs in Village 2 during the dry (harvest) season followed by the post-harvest season. This is not anticipated as we would expect households to be increasing in food security during this time; however, Giroux *et al* (2020) found higher levels, in terms of value, of commodities (mainly food) shared during the post-harvest period in Kenya and deemed it could reflect increased ability to give commodities post-harvest due to renewed food storage (Giroux *et al* 2020). Like Village 1, Village 2 could experience shortage of goods during dry (harvest) season, increasing sharing, but then renewed food storage as found in the Giroux *et al* (2020) study in post-harvest season, promoting sharing.

The peaks in labor sharing of both villages are likely attributed to increased agricultural labor demand during planting season and dry (harvest) season. We speculate that the greatest density of the livestock sharing networks occurs during the planting season in both villages because of the increased need for livestock for agricultural tools, such as oxen carts. There is less livestock sharing (i.e. lower densities for livestock), which could be attributed to high livestock ownership in the province, leading to less need to share livestock.

The structure of maize sharing between the two villages differs. The seasonal difference of when the greatest density and greatest mass is shared in Village 1 indicates that larger masses of maize are shared between fewer households during the dry season, and smaller quantities of maize are exchanged between many households in the planting season. The lower

Table 8. Poisson Pseudo-Maximum Likelihood Estimator gravity model results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log of inc_i	0.461**	0.660**	0.657**	0.654**	0.637**	0.481**	0.196
	(0.151)	(0.203)	(0.204)	(0.205)	(0.225)	(0.159)	(0.205)
log of inc_j	−0.0302	0.0690	0.0615	0.0695	0.163	0.175	0.341
	(0.125)	(0.144)	(0.143)	(0.146)	(0.143)	(0.155)	(0.200)
log of *distance*	−0.662***	−0.853***	−0.778***	−0.780***	−0.748***	−0.849***	−0.801***
	(0.0979)	(0.0881)	(0.134)	(0.131)	(0.135)	(0.191)	(0.173)
village		1.962***	1.824**	1.721**	1.550**	2.208**	1.594*
		(0.583)	(0.641)	(0.637)	(0.495)	(0.710)	(0.795)
related			0.507	0.567	0.628	0.733	0.859
			(0.594)	(0.543)	(0.571)	(0.552)	(0.522)
log of $market_i$				0.224	0.209	−0.0949	−0.0286
				(0.163)	(0.171)	(0.214)	(0.227)
log of $market_j$				−0.187	−0.160	−0.197	−0.156
				(0.230)	(0.238)	(0.236)	(0.209)
$storage_i$					0.240	−0.181	−0.537
					(0.576)	(0.583)	(0.480)
$storage_j$					−2.210**	−2.016**	−1.905*
					(0.677)	(0.680)	(0.762)
log of $land_i$						0.904	0.445
						(0.686)	(0.745)
log of $land_j$						−0.383	−0.360
						(0.312)	(0.316)
log of fcs_i							2.995*
							(1.241)
log of fcs_j							−1.428
							(0.748)
Constant	−3.564***	−6.975***	−6.907***	−6.927***	−7.211***	−7.303***	−12.05***
	(1.001)	(1.680)	(1.681)	(1.800)	(1.733)	(1.406)	(3.483)
Observations	2830	2830	2830	2830	2830	2632	2632
R^2	0.005	0.015	0.015	0.021	0.024	0.047	0.091

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

network densities of maize sharing could be attributed to the above average maize production nationally during the 2016/2017 season which surpassed the national cereal demand by over 1 million metric tons (Famine Early Warning Systems Network 2017). Moreover, the higher-than-average maize yields of the 2016/2017 season brought maize prices down, which led farmers to sell smaller volumes resulting in more household maize storage (Famine Early Warning Systems Network 2017). This also could have contributed to the lower maize network densities relative to other sharing categories. It should be noted that these larger masses are not specific to the southern region.

The regression results suggest distance is negatively associated with household maize exchanges; the greater the distance is between households, the less likely the households will share. As we might anticipate, if a recipient household has maize in storage, then they are less likely to receive shared maize. The food consumption scores of both the donor and recipient households behave in the anticipated manner. The donor households food consumption scores are positively associated with household maize exchange and statistically significant, indicating that a household supplies more maize if it has a higher food consumption score, i.e. it is more food secure. On the contrary, an increase in recipient households food consumption scores is associated with a decrease in household maize exchange, suggesting that the household is more food secure and thus would be less likely to receive maize.

The magnitude of the coefficients of distance and donor households income is smaller compared to the coefficients of the variables specific to trade at this scale, suggesting distance and donor households income has less of an impact on the value of maize exchanged than village, recipient households maize storage, the food consumption score of donor and recipient households.

4.2. Data-driven approach for modeling household sharing

This study seeks to understand how household-level food sharing compares with global food trade. We find that two data-driven approaches to modeling international trade are applicable to household sharing; namely, social network statistics and the gravity model. Taken together, these approaches

Table 9. Logit gravity model results.

	(Food)	(Maize)	(Livestock)	(Non-Food)	(Labor)
Intercept	1.3670	-2.8240^{*}	-0.0220	-2.0991^{*}	0.4178
	(0.722)	(1.216)	(1.1771)	(0.850)	(0.800)
log of distance	-1.2360^{***}	-0.8757^{***}	-0.7672^{***}	-0.9711^{***}	-1.0516^{***}
	(0.098)	(0.141)	(0.140)	(0.105)	(0.104)
log of $income_d$	0.1870^{***}	0.1291	0.0853	0.3199^{***}	0.0778
	(0.055)	(0.096)	(0.088)	(0.074)	(0.056)
log of $income_r$	0.1513^{**}	0.1162	0.1011	0.1477^{*}	0.2687^{***}
	(0.053)	(0.088)	(0.084)	(0.061)	(0.069)
village	0.6437^{*}	1.205^{*}	0.6424	1.2770^{***}	0.6439
	(0.323)	(0.541)	(0.594)	(0.380)	(0.373)
related	1.6750^{***}	1.4180^{***}	1.3482^{***}	1.0512^{***}	1.4351^{***}
	(0.193)	(0.342)	(0.337)	(0.223)	(0.219)
$maizeland_i$	0.0863	0.0470	0.0165	0.0809	-0.0353
	(0.053)	(0.080)	(0.066)	(0.049)	(0.065)
$maizeland_j$	0.0457	-0.1134	-0.1595	-0.0367	0.0322
	(0.052)	(0.095)	(0.127)	(0.064)	(0.054)
$maizestorage_i$	-0.7442^{**}	-0.6803	0.7046	-0.2283	0.0735
	(0.250)	(0.417)	(0.414)	(0.262)	(0.277)
$maizestorage_j$	-0.4713	-1.074^{*}	0.5036	-0.1288	-0.0362
	(0.250)	(0.546)	(0.457)	(0.280)	(0.260)
$totalland_i$	-0.0557	0.0575	0.0771	0.0638	-0.0273
	(0.051)	(0.079)	(0.065)	(0.049)	(0.052)
$totalland_j$	-0.0345	0.0885	0.0085	0.0011	0.0213
	(0.048)	(0.071)	(0.072)	(0.050)	(0.051)
$time_i$	0.0000	-0.0002	0.0084	0.0060	-0.0008
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
$time_j$	-0.0039	-0.0059	0.0043	-0.0005	0.0011
	(0.003)	(0.004)	(0.005)	(0.003)	(0.0033)
fcs_i	0.01 334	0.0300^{**}	-0.0158	-0.0001	0.0021
	(0.007)	(0.012)	(0.012)	(0.008)	(0.008)
fcs_j	0.0072	0.001 189	-0.0296^{*}	0.0058	-0.0027
	(0.007)	(0.011)	(0.013)	(0.008)	(0.008)
Null Deviance	1422.2	556.87	524.14	1108.45	1095.84
Residual Deviance	1053.2	429.16	422.32	868.42	858.49

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. Maize sharing flow spatial Poisson ML and aspatial Poisson ML results.

	SAR-Poisson		Poisson ML	
	Coefficients	S.E.	Coefficients	S.E.
ρ	0.154^{**}	0.046		
Intercept	2.378^{***}	0.197	3.050^{***}	0.045
log of *income*	0.069^{***}	0.007	0.057^{***}	0.006
village	0.691^{***}	0.036	0.782^{***}	0.028
maizeland	-0.036^{***}	0.006	-0.048^{***}	0.005
maizestorage	-0.663^{***}	0.033	-0.692^{***}	0.030
farmland	0.109^{***}	0.005	0.112^{***}	0.005
time	-0.002^{***}	0.0003	-0.002^{***}	0.0003
fcs	0.013^{***}	0.001	0.015^{***}	0.0007
Log Likelihood	41 188.5		41 182.96	
Pseudo R^2	0.233		0.225	

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

to modeling commodity exchanges help us to comprehensively perform link prediction and intensity estimation, which is particularly important for locations without data. For example, the framework developed by Konar *et al* (2018) and Lin *et al* (2019) to model food flows constraints the cost objective linear programming by logit gravity model for link prediction and Gamma distribution flows assignment. This study supplements research on supply chain modeling by showing that the gravity model is relevant at micro scales and to the African context. Our research supplements the theoretical foundation of commodity flows modeling, by verifying that maize sharing can be treated as a Poisson process.

4.3. Limitations

We implemented the surveys during the time of year when most households are harvesting maize. Some households were in the midst of harvest, while others had already completed their harvest for the season. This timing would portray the villages as more food secure than they would have been during previous seasons. Food consumption score captures one specific week while the exchanges are recorded for a longer time period. We do not have high temporal resolution data which is important because food security fluctuates considerably throughout the year. Another limitation of the study is accurate recall of sharing events and food consumption. As with all primary data comes the risk of inaccurate reporting which can present inconsistencies in the data. For future studies, the villages should be surveyed more frequently especially at the end of each agricultural season (i.e. dry, planting, rainy, and post-harvest) to better ensure accurate recall and to capture seasonal changes in food security. We were also only able to capture around 80 percent of each network, not the full network. Capturing the full network is very difficult in the field. We attempted to capture as complete of a network as possible by allowing households to indicate whether they supplied and/or received with a non-surveyed household as missing network data may affect structural measures (Borgatti *et al* 2006, Smith and Moody 2013, Smith *et al* 2017).

Food sharing cannot be solely explained by economic or ecological variables, and there is considerable cross-cultural variation in sharing (Ahedo *et al* 2019, Quandt *et al* 2001, Tatebayashi *et al* 2019, Tucker 2004). Food sharing may be part of symbolic gestures, as in the case of contributions after the death of a family member, to exchanges that are part of a more regular effort to support a chronically food insecure household. For example, among groups of Maasai, group solidarity is bound up with sharing among community members and plays a role in ritual (Ahedo *et al* 2019, Talk 1987). Food resources and sharing are associated with social status (Wiessner *et al* 1996), generosity (Gurven *et al* 2000), genotypic traits (Bird *et al* 2001), and used to support alliance building (Patton 2005). In some cases, kinship has been identified as a major driver of food sharing but in other social structures strong cultural or group norms obligate individuals to help others in need, regardless of kinship ties (Gurven 2004). Cultural conditions related to empathy, altruism, support and sharing are often described as key values on which traditional ecological knowledge and practices are developed (Berkes 2009, Finn and Jackson 2011). More recently, digital platforms to facilitate food sharing that allow for what appear to be purely altruistic motivations have emerged (Michelini *et al* 2018).

5. Conclusion

This paper surveyed farming households in Zambia to understand inter-household sharing. We have shown how commodity sharing is influenced by many household-level and contextual factors, yet a general gravity model approach can reproduce fundamental commodity sharing relationships. The gravity model applies despite significant differences in how networks of food sharing function in each village. In this way we highlight the multiple scales at which food sharing can be understood and the importance of considering these different scales in thinking about policy to improve food systems. To our knowledge, this is the first study to apply the classic gravity model of trade—established for market-driven international trade between nations—to household sharing of goods within a village. Geographic distance between households and the income of sharing households play analogous roles to geographic distance between nations and country-level GDP in the classic gravity model of trade. This indicates that certain drivers of food exchange systems are similar across vastly different scales of analysis. Future studies on household food sharing could take these gravitational features into account in order to understand the spatial and social nature of sharing relationships.

We also show that the network structure of food sharing in Zambia is consistent with other food flow systems in villages, nations and internationally (e.g. those presented in Baggio *et al* (2016), Konar *et al* (2018)). Specifically, we showed that maize mass fluxes follow a Gamma distribution and that the relationship between mass flux and household connectivity has a power law structure. This indicates that structural network properties are consistent across dramatically different food sharing systems, which means that similar mechanisms may be at play. This work contributes to a body of literature that seeks to understand and model food flows in a variety of locations and across scales. Understanding that the statistical distribution of food fluxes are invariant across spatial scales contributed to a model of food flows in the United States (Lin *et al* 2019).

Future work can build on the findings of this study to model sub-national agri-food fluxes throughout Sub-Saharan Africa. Additionally, future research could strive to uncover a theoretical model that is capable of generating the observed network features. This will allow us to better understand the generative mechanisms leading to these food flow network structures. Understanding the structure and functioning of food exchange systems—such as household sharing—will enable us to evaluate how and where sharing will serve as an adaptation measure to future production shocks.

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