Need-Based Transfers Enhance Resilience to Shocks: An Agent-Based Model of a Maasai Risk-Pooling System

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Abstract

Maasai and other Maa-speaking pastoralists in Kenya and Tanzania have a risk-pooling system that they refer to by their word for the umbilical cord (*osotua*). Gifts from one osotua partner to another are contingent on the recipient's need and do not create any debt. We refer to such gifts as need-based transfers. Maa-speakers also have a system of debt-based transfers (*esile*) in which gifts must be repaid. We designed an agent-based model to compare the impacts on herd survival of need-based and debt-based transfers on networks of varying topologies and sizes and with different degrees of temporal correlation of shocks felt by the agents. We found that the use of need-based rather than debt-based transfers, greater network modularity, greater network size, and decreased correlation among shocks were associated with increased rates of survival.

Keywords Social networks · Risk pooling · Agent-based modelling · Need-based transfers · Small-scale societies · Kenya Tanzania

Introduction

To pool risk, Maasai and other Maa-speaking pastoralists in Kenya and Tanzania have a livestock-sharing system involving partnerships that they refer to by their word for umbilical cord: *osotua* (plural *isotuatin*; Cronk, 2007; Aktipis *et al.,* 2011, 2016; Hao *et al.,* 2015a; Cronk *et al.,* 2019). Many osotua partnerships begin in childhood. Maasai parents encourage their children to form friendships known as *isirito* (singular: *esirit*). Isirito share food and exchange small gifts that may become more valuable as they become adults. If both parties agree, they then become isotuatin. Isotuatin rely on each other for help in times of need. For example, if a herder does not have enough livestock to support his family, he may ask one of his osotua partners for enough to bring his family up to the level necessary for survival. Transfers between osotua partners create neither credit nor debt, and Maasai interviewees insist that the concept of payment should never be invoked in an osotua relationship and that there is no expectation of balanced transfers even in the long run. Transfers occur only in response to requests, and requests must arise from genuine need and must be limited to the amount actually needed. Osotua relationships are imbued with respect, restraint, and a sense of great responsibility (Cronk, 2007; Cronk *et al.,* 2019).

People often try to establish osotua partnerships with people in different ecological zones so that their risk profiles are complementary (see also Gulliver, 1955; Dixit *et al.,* 2013). For example, highland areas are relatively well-watered, but they harbor more pathogens than do dryer lowland areas. Unfortunately, droughts and other calamities sometimes affect large areas. As a result, an individual herder may have trouble finding any isotuatin who are able to help. Such a situation of highly correlated shocks occurred among the Maasai during a nineteen-year period in the late 19th and early twentieth centuries that they refer to as *Emutai*, meaning, roughly, "the wiping out" (Waller, 1988). Emutai was caused by a combination of drought and epidemics among both humans and their livestock and led to a breakdown of social relations and civil war among Maasai sections.

In addition to osotua, Maasai and other Maa-speakers have several other rules that govern property transfers in a variety of specific circumstances. Among Maasai living in Ngorongoro, a clan-based system of aid through livestock transfers called *engelata* (i.e., "choice," Mol, 1996:79) has been documented (Potkanski, 2000). Several varieties of engelata exist. *Engelata enkaputee* (i.e., of the affines) is

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a way to raise bridewealth. *Engelata ewoloto* is a way for a clan to help a destitute family. The Maa-speaking Samburu of northern Kenya refer to the lending of a cow's milk to another household as *keruu* and the lending of the cow itself as *ketaaro*, while *aitogaroo* refers to the loan of a bull for breeding purposes, and *ketapashaki* refers to the immediate exchange of two animals, e.g., a steer for a cow. Livestock may also be transferred in the form of bridewealth and as compensation for crimes (Perlov, 1987; Potkanski, 2000). One type of livestock transfer that contrasts sharply with osotua is *esile*, which translates simply as "debt." In esile, unlike in osotua, credit and repayment of debts are the essence of the relationship: both parties expect that the debt will be repaid. "An esile is like a bank" is a common expression among the Samburu that captures this idea (Perlov, 1987:186). As with bank loans, esile transfers, unlike ketapashaki, involve a delay between the loan and its repayment. Common reasons for requests of esile are the desire to make some cash by selling livestock or because one needs a specific type of animal that one does not already have for a particular ceremony.

Because many other pastoralist societies also have sharing rules equivalent or similar to osotua and esile (Almagor, 1978; Bollig, 1998, 2006; Dyson-Hudson, 1966; Flannery *et al.,* 1989; Gulliver, 1955; Iyer, 2016; Moritz, 2016; Moritz *et al.,* 2011), we henceforth follow Aktipis *et al.* (2016) and Cronk *et al.* (2019) in using a more general, less Maasai-specific set of terms, referring to osotua as "need-based transfers" and esile as "debt-based transfers."

Four previous efforts have been made to use computer simulations to model aspects of Maasai-style risk-pooling networks. In all of these simulations, agents begin with an amount of livestock that is slightly above a fixed threshold for survival. Agents who drop below that threshold for a predetermined number of rounds (e.g., two) drop out of the simulation and are considered to have not survived, although in the real world such impoverished herders might instead supplement herding with other food sources such as hunting, gathering, and farming. During each round, herds grow, but they may also experience losses that simulate the impacts of droughts, diseases and thefts. Agents are also programmed with decision-making rules for how and when to transfer cattle that vary from simulation to simulation. Aktipis *et al.* (2011) created an agent-based model in which agents endowed with herds that grew and experienced occasional negative shocks were paired with each other in dyads. The model included four types of agents: (1) those that followed a need-based transfer rule (i.e., ask when in need, give if able); (2) those that never transferred anything; (3) those that asked their partner for cattle at a rate equivalent to the average asking rate among agents following a need-based asking rule and who requested a number of cattle equivalent to the

mean amount given by agents in the need-based transfer runs; and (4) those that, when asked for help, gave a proportion of their cattle that was equivalent to the average mean proportion given in the need-based transfer runs. Agents following the full need-based transfer rule survived longer than all other types of agents. Aktipis *et al.* (2016) also placed agents in dyads, finding that agents following need-based transfer rules outperformed those following debt-based transfer rules.

Different network features and correlation of disasters can affect the outcomes for agents sharing on networks using need-based transfer rules. Hao *et al.* (2015a, b) found that agents arranged in a network and following a need-based transfer rule survived longer when those in need asked their wealthiest partner rather than a partner chosen at random and that greater network connectedness improved survival. Hao *et al.* (2015, b) found that temporal correlation of disasters decreased the survival of need-based agents while spatial correlation of disasters improved their survival. The authors attributed the improvement in survival when disasters are spatially correlated to a phenomenon they label "disaster masking": A given disaster is likely to kill only a small, highly localized group of agents, leaving the rest to thrive while also clearing agents out of a location where additional disasters are likely to strike in the future.

In the present paper, we build upon this previous work to address several questions. Like Hao *et al.* (2015a) and Hao *et al.* (2015b), we model agents on a network, but we also vary both network size and network topology. Like Hao *et al.* (2015b), we examine temporally correlated disasters: It is clearly better if agents do not experience shocks simultaneously, but where is the threshold at which temporal correlation spells doom, and does that threshold change depending on the settings of the other parameters? Finally, like Aktipis *et al.* (2016) we compare the survival of need-based transfer agents with that of debt-based transfer agents, but here we vary the sizes and topologies of social networks as well as the temporal correlations of disasters. Giving to those in need, often with no expectation of repayment, is found not only in the Maasai osotua system but also in many other risk-pooling systems documented ethnographically in small-scale societies around the world, which indicates that it may be adaptive in a wide variety of ecological and economic circumstances (Bird *et al.,* 2002; Bollig, 1998, 2006; Cashdan, 1985; Cronk *et al.,* 2019; Fafchamps, 2011; Fafchamps & Lund, 2003; Gulliver, 1955; Iyer, 2016; Smith *et al.,* 2019; Wiessner, 1982). Here we investigate the performance of need-based transfer and debt-based transfer strategies on three different network topologies: regular networks, small-world networks and preferential attachment networks.

We tested the following hypotheses:

1. Agents following a need-based transfers rule will survive longer than agents following a debt-based transfer rule.
2. Agents in larger networks will survive longer than agents in smaller networks.
3. Agents in more modular networks will survive longer than agents in less modular networks.
4. Agents that experience shocks that are less correlated temporally with shocks experienced by other agents in their networks will survive longer than agents that experience shocks that are more correlated temporally with shocks experienced by other agents in their networks.

Methods

We used NetLogo (Wilensky, 1999) to model a population of agents in networks with varying topologies (see Fig. 1). We included regular networks, small-world networks, and preferential attachment networks in our simulations. In regular networks, all individuals are connected to the same number of individuals within the network. In a small-world network, there are a number of connections that span across the network, leading to the phenomenon seen in the real world in which strangers can be linked through a small chain of acquaintances. We also included preferential attachment networks. Using the Barabási and Albert model (Barabási & Albert, 1999), we generated random scale-free networks using a preferential attachment mechanism, which preferentially adds connections to nodes that are already well connected (see glossary).

As in Aktipis *et al.* (2011, 2016) each node/agent in the network represents a household/family of approximately six individuals, and each link represents a connection to another household. The model is parameterized based on the ecology of East Africa, and the rules that agents use are based on the osotua (need-based transfer) and esile (debt-based transfer) rules used by Maasai.

During each time step (representing a year), households experience herd growth and potential shocks and losses. They also have an opportunity to ask for and give help to other households (see Fig. S1). An agent's initial herd of 70 grows or shrinks during each time step of the simulation at a rate normally distributed around a mean of 3.4%. The minimum viable herd size was set at 64, based on estimates of a family's caloric needs and productivity in the dry season. The maximum cattle herd size allowed in the model is 600, which represents a realistic approximation of the maximum cattle herd size for an average-sized household. During each time step there is also a chance of a loss (e.g., through a drought or a disease spreading in the herd). All of these parameters, including the likelihood and severity of these losses, were estimated based on Dahl and Hjort's study of the actual dynamics of East African cattle herds (1976).

The model was run for 100-time steps. Across models we vary the probability, p_{shocks}, that a loss is correlated (i.e., it affects all households at the same time) from 0 to 1 with steps of 0.1.

We simulated both need-based and debt-based livestock transfers between households as follows:

Need-based transfer rule: Need-based transfer agents monitor their livestock holdings. If they drop below the critical threshold for livestock holdings, they ask their wealthiest partner for help (i.e., agents used a selective asking rule rather than a random asking rule as in Hao *et al.,* 2015a); if they are asked for help and can afford to provide it without putting themselves below the critical threshold for survival, they do so. The pseudo-code (i.e., a description in natural language rather than computer code) for the need-based transfer rules were implemented as follows (as in Aktipis *et al.,* 2016, Aktipis *et al.,* 2011, and Hao *et al.,* 2015a):

1. **Need-based asking rule**: Individuals ask their partners for livestock only if their current holdings are below the asking threshold (i.e., the minimum herd size of 64).
2. **Need-based giving rule**: Individuals give what is asked, but not so much as to put their herds below the giving threshold (also the minimum herd size of 64).

Debt-based transfer rule: Debt-based transfer agents also ask their wealthiest partner for help when they are in need, but otherwise, they differ from need-based transfer agents. Debt-based agents transfer cattle only if they are asked by a partner who is in good standing. These debt-based agents keep track of the amounts they owe to and were owed by the other agents in their networks. Recipients of loans repay these loans as soon as they have enough livestock to do so without going below the sustainability threshold of 64 units. If five rounds go by after a transfer without repayment, then the agent who gave the loan considers the 'defaulting' partner to no longer be in good standing and therefore does not provide a loan to that agent in the future. The pseudo-code for this rule is as follows:
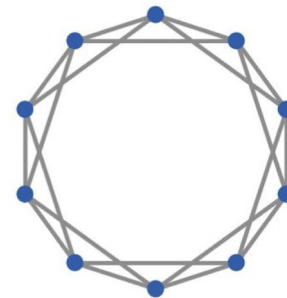
1. **Debt-based payback rule**:

   If livestock have been previously transferred from the partner to the actor and the actor has enough to pay back without going below the sustainability threshold (*resource min*), the actor pays livestock back to his partner according to the actor's *repayment probability*
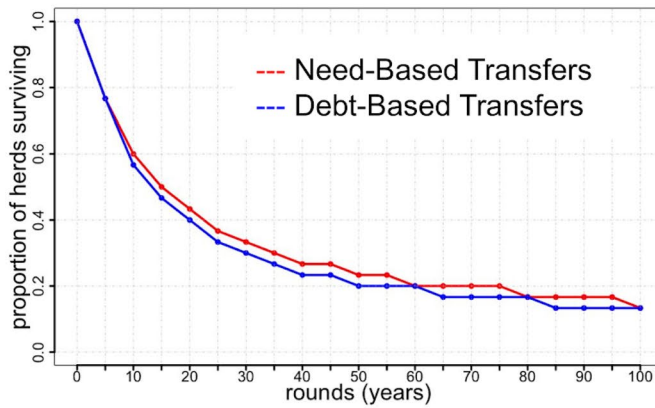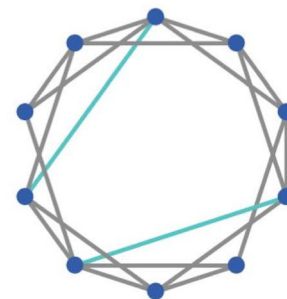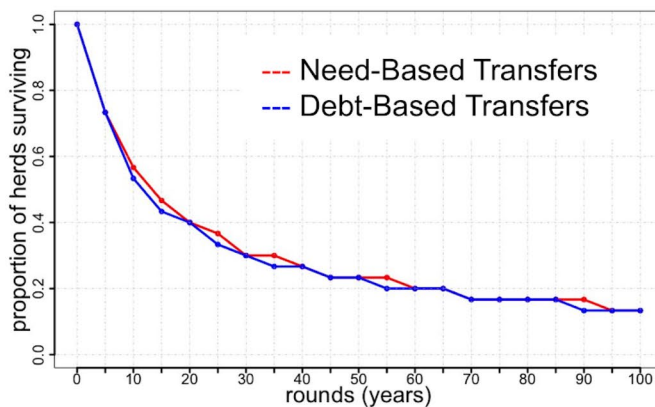
N = 30

a
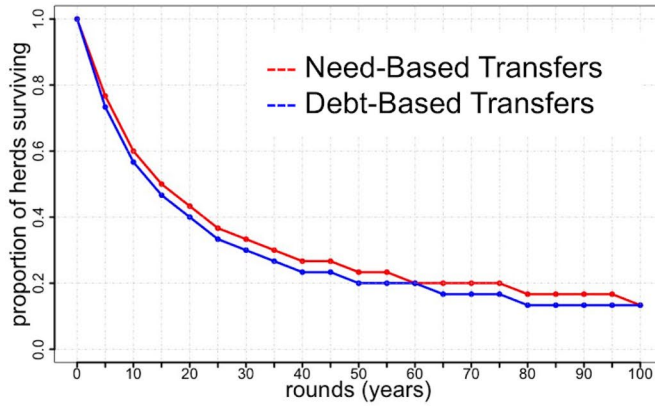
Regular

b

Small world
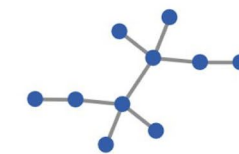
c

Preferential attachment

◄**Fig. 1** Proportion of herds surviving (y-axis) as a function of time (x-axis), for three network topologies (regular, small-world and preferential attachment), N = 30, when there is no correlation of shocks. Need-based agents significantly outperform debt-based agents across all network topologies (see Table 3 and Tables S1-S5)

2. **Debt-based partner credit check rule**:

   Checks whether a partner is in good standing, which includes not having exceeded *tolerated delay* or *credit size* (when applicable)

3. **Debt-based asking rule**:

   As with the need-based transfer asking rule, individuals ask their partners for livestock if their current herd size is below the sustainability threshold of 64.

4. **Debt-based giving rule**:

   Response to partner. If a request is made, actors give if two conditions are met:

   1. If no debt remains from a previous request and the partner is in good standing (meaning that previous debt had not existed for longer than *tolerated delay*)
   2. The amount transferred cannot exceed the *credit size* extended to the partner

We varied four key parameters while keeping all other aspects of the simulations constant:

(1) Network topology: regular, small world, and preferential attachment.
(2) Network size: values of 30, 40, 50, 60, 70, 80, 90, and 100.
(3) Correlation of shocks: probabilities of 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.
(4) Sharing rule: need-based transfers vs. debt-based transfers.

This yielded a total of 528 unique combinations of parameters for our simulations. For each of these 528 combinations of parameters, we ran the model 10,000 times.

Results

We varied four parameters: network topology, network size, sharing rule, and correlation of shocks. For each combination of these parameters, we tested the performance of two resource transfers rules, i.e., a need-based strategy and a debt-based strategy. Unless otherwise specified, all results

refer to small-world networks, which are the default type of network used for these kinds of studies. Also, in the graphical presentation of our results, we often show only a subset of the full data because it is impossible to show the full dimensionality of the data given that we varied four parameters (network topology, network size, correlation of shocks, and the sharing rule).

In a separate set of simulations, we varied tolerated delay, sampling values from one year to 50 years of tolerated delay. The tolerated delay parameter is relevant only to debt-based transfer agents; it specifies how long they will wait to get paid back before refusing to interact with that partner again. Results show that the impact of variations in the tolerated delay is minimal compared to the impacts of the other parameters we varied. We, therefore, set tolerated delay at five years, which is in line with our previous publication (Aktipis *et al.,* 2016).

Here we report the survival of agents (i.e., households), as a proxy for the ecological viability of these strategies. However, we have also run evolutionary versions of the model (i.e., versions in which agents can reproduce), and we present preliminary results from those simulations in the Supplementary Information (Fig. S2).

We used two different measures to evaluate the performance of the two sharing strategies. First, we calculated the ratio of runs resulting in the survival of at least one agent from the initial population of N agents at the end of the runs (time step 100). This is a measure of the effectiveness of adopting a specific sharing strategy given a set of conditions (i.e., network topology, group size, and correlation of shocks). Given a specific combination of parameters, this ratio is expressed as the number of runs ending with at least one surviving agent over the total number of runs (i.e., 10,000 runs). Second, we examined the proportion of herds surviving at the end of each run (time step 100) calculated for each combination of the parameters as the median value from all 10,000 runs over the initial N. Finally, because the simulations' results are not normally distributed and because our sample size is so large that p-values alone may not be sufficient to draw strong conclusions from our results, we have included two additional analyses. One of these is a Mann Whitney U test (Hollander & Wolfe, 1973) (the results of which are presented throughout this section and in Supplementary Information), and the other is a report simply of all of the conditions in which the survival advantage of the need-based strategy is greater than 5% over the debt-based strategy (presented at the end of the results section).

We used the Mann–Whitney U statistic to test whether the need-based strategy has stochastic dominance compared with the debt-based strategy. This allows us to verify the null hypothesis that results from both strategies follow the same distribution, quantifying the probability that a randomly

selected datum from a first set of results (e.g., the need-based strategy results) is higher or lower than another datum randomly selected from a different set of results (e.g., the debt-based strategy results). Some differences between the performance of the strategies in the model are small, and the ρ statistic allows us to evaluate whether the effect size is meaningful.

The ρ statistic has values ranging from zero to one. A value of 0.5 means that the two sets of data overlap. The closer it is to 1, the greater the stochastic dominance of the first set of results; the closer it is to 0, the greater the stochastic dominance of the second set of results. To define the statistical significance of the values obtained by running the Mann–Whitney U test, we have combined the ρ statistic and p-values to derive a cut-off. If the value of the ρ statistic is between 0.49 and 0.51, we considered this a confirmation of the null hypothesis that two distributions of data overlap and therefore, there is no difference in the performance of the need-based and debt-based strategies.

Network Topology

Regardless of network topology, agents using the need-based rule outperform agents using a debt-based rule when shocks are uncorrelated. In Fig. 1 we show the proportion of herds surviving over time as the simulations progress. Table 1 shows the proportion of runs ending with at least one surviving agent (see also Table 3 and Tables S1-S2 in Supplementary Information, which provides a measure of the effect size calculated as ρ from the Mann Whitney U test). If we compare survival across different network topologies, we can see that more agents in preferential attachment networks survive, on average, than do agents in regular and small-world networks when N < 50 (see Table 1). The improvement in survival for agents in modular preferential

attachment networks (compared to other networks) is significant for agents following either transfer rule (see Fig. 1a, c and the first row of Table 1). In preferential attachment networks, sub-groups of nodes are highly interconnected within groups but loosely connected outside them, which can help to limit the impact of shocks on the network as a whole. As a result, the difference in performance between need-based and debt-based systems is smaller for the preferential attachment network structure compared to other network structures (this difference in performance is also limited to no correlation of shocks and networks of small size, i.e., N < 60 when the correlation is 0.1 and N < 40 when the correlation is 0.2. See Table S2 in Supplementary Information for details about the effect size as ρ from the Mann Whitney U test).

Although, on average, the proportion of runs ending with at least one surviving agent is the same for both strategies when N > 30 (see rows 2 and 3 in Table 1), Mann Whitney U test effect size ρ shows that, when shocks are uncorrelated, the need-based rule stochastically dominates the debt-based rule for all values of N (Mann Whitney U test $\rho > 0.51$ and p-value < 0.05 in all cases, except for preferential attachment networks with N = 80, where $\rho = 0.508$, but p-value < 0.05; see first column of Tables 3, S1-S2, and first column of Tables S3-S5).

Network Size

In order to see how the size of a network affects the ability of agents to survive, we considered a small-world network, $p_{shocks} = 0.1, 0.5$, and 1, and varied network size (see Fig. S3a-f and Table 2). Particularly for networks with N < 100 and low correlation of shocks ($p_{shocks} = 0.1$), agents following a need-based transfer rule significantly outperformed those following a debt-based transfer rule (Mann Whitney U test derived $\rho = 0.553$ when N = 30, $\rho = 0.546$

Table 1 The proportion of runs ending with at least one surviving agent at time round = 100, varying the size of the networks (N = 30, 50, 100). This table shows a subset of the results obtained by systematically varying N. NBT = need-based transfer rule, DBT = debt-based transfer rule

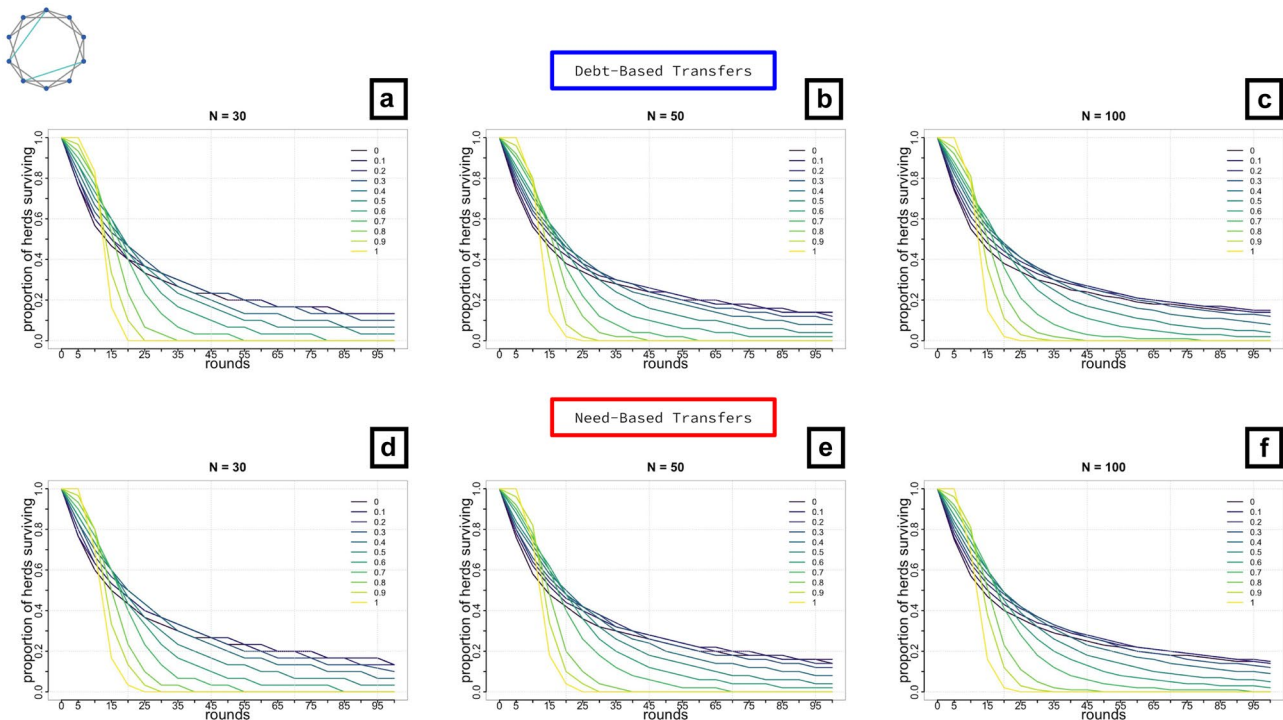| N	Regular NBT	Regular DBT	Small World NBT	Small World DBT	Preferential NBT	Preferential DBT
30	0.983	0.973	0.985	0.972	0.99	0.985
50	0.999	0.999	0.999	0.999	1	0.999
100	1	1	1	1	1	1

Fig. 2 Proportion of herds surviving for agents using debt-based (a-c) and need-based (d-e) strategies in small world networks for three different network sizes (N = 30, 50, 100). The figure shows the proportion of herds surviving (y-axis) as a function of the correlation of shocks.

Need-based strategies outperform debt-based strategies for networks of size N = 30, 50, 100 and correlation of shocks < 0.5 when N = 30, 50 and correlation of shocks < 0.3 when N = 100 (Mann Whitney U test ρ > 0.51; see Tables 2 and 3 for details)

when N = 50, and $\rho = 0.519$ when N = 100; see Table 3, and Table S3 for details). As network size increases, survival rates increase for agents following both rules, though the need-based rule continues to perform better than the debt-based rule as long as the correlation of shocks is low or intermediate (see Table 2a and the second column of Table 3 for Mann Whitney U test ρ values). As the correlation of shocks increases, the survival of both strategies diminishes, and the advantage of the need-based strategy over the debt-based strategy becomes smaller and eventually not significant (see Table 2b and sixth column of Tables 3 and S3).

When shocks are completely correlated ($p_{shocks} = 1$), the Mann–Whitney U test reveals that the performances of the need-based and debt-based strategies are not different (see Table 2c and last column of Tables 3 and S3).

Correlation of Shocks

If everyone in a social network experiences a severe shock simultaneously, no one may be in a position to help anyone else. To investigate the effects of synchronicity of shocks, we investigated three network sizes (N = 30, 50, 100) and varied the correlation of shocks

($p_{shocks} = [0,1]$) from a scenario in which all shocks are uncorrelated (i.e., an idiosyncratic scenario) to a scenario in which all shocks are completely correlated (i.e., a systemic scenario), affecting all agents at the same time (see Fig. 2). This probability, p_{shocks}, is the likelihood that a shock will affect all agents in a network at the same time. When $p_{shocks} = 0$, a shock is likely to affect just a single agent in the network at time t. At the other extreme, when $p_{shocks} = 1$, all agents from the same network are affected by the same shock at the same time. We also considered intermediate scenarios by varying the probability of correlated shocks from 0 to 1 by steps of 0.1. For low levels of correlated shocks, need-based agents outperform debt-based agents (Mann Whitney U test ρ values > 0.51 for all values of N, when $p_{shocks} < 0.3$; ρ values > 0.51 for N < 80, when $p_{shocks} < 0.5$; ρ values > 0.51 for N < 60, when $p_{shocks} < 0.7$; see Tables 3 and S3 for details). As the probability of correlated shocks increases, survival of agents decreases, and both strategies perform equally poorly when the probability of correlated shocks is higher than 0.7 (see Table 2 showing the proportion of runs ending with at least one surviving agent considering $p_{shocks} = 0.1, 0.5, 1$ and Table 3 showing the effect

Table 2 The proportion of runs resulting in the survival of at least one agent, varying the size of the networks (N = 30, 50, 100) and the correlation of shocks (p_{shocks} = 0.1, 0.5, 1, in panels a, b, c, respec-tively). This table shows the results obtained by systematically vary-ing N and p_{shocks}. NBT = need-based transfer rule, DBT = debt-based transfer rule

a

N	Regular NBT	Regular DBT	Small World NBT	Small World DBT	Preferential NBT	Preferential DBT
30	0.877	0.862	0.876	0.861	0.896	0.889
50	0.909	0.908	0.917	0.904	0.933	0.931
100	0.936	0.936	0.942	0.937	0.945	0.942

(panel label: **0.1**)

b

N	Regular NBT	Regular DBT	Small World NBT	Small World DBT	Preferential NBT	Preferential DBT
30	0.549	0.522	0.537	0.533	0.578	0.577
50	0.583	0.57	0.583	0.574	0.615	0.623
100	0.636	0.622	0.626	0.622	0.655	0.639

(panel label: **0.5**)

c

N	Regular NBT	Regular DBT	Small World NBT	Small World DBT	Preferential NBT	Preferential DBT
30	0.241	0.239	0.24	0.24	0.25	0.256
50	0.265	0.251	0.261	0.253	0.266	0.274
100	0.284	0.273	0.276	0.28	0.292	0.287

(panel label: **1**)

size ρ from the Mann Whitney U test: when $p_{shocks} > 0.7$ neither strategy stochastically dominates $\rho < 0.51$, except for the specific combination of parameters N = 60 and $p_{shocks} = 0.8$).

Conditions in which the Survival Advantage is Greater than 5% for Need-Based vs. Debt-Based Strategies

In order to identify the combinations of conditions in which the difference between need-based and debt-based strategies is largest, we considered all the combinations of parameters in which need-based agents had at least a 5% survival advantage over the debt-based agents. We calculated the difference of median herds surviving at the end of the simulations (t = 100) (see Eq. 1).

$$advantage_{NBT \ over \ DBT} = \frac{M_{i,j}^{NBT} - M_{i,j}^{DBT}}{M_{i,j}^{DBT}} \qquad (1)$$

where $M_{i,j}^{NBT}$ is the matrix of the median herds surviving of need-based strategy networks at the end of the simulations

in which columns stay for different values of p_{shocks} (from 0 to 1 by 0.1) and rows represent network size (from 30 to 100 by 10);

$M_{i,j}^{DBT}$ is the matrix of the median herds surviving of debt-based strategy networks at the end of the simulations in which columns stay for different values of p_{shocks} (from 0 to 1 by 0.1) and rows represent network size (from 30 to 100 by 10);

and $M_{i,j}^{DBT} > 0$.

Small World Networks

We found that, in small world networks, when the probability of concurrent shocks is low ($p_{shocks} < = 0.2$), the need-based rule outperforms the debt-based rule by 5% or more in 50% of cases. When the probability of concurrent shocks is intermedi-ate ($0.3 < = p_{shocks} < 0.5$) need-based agents have an advantage of 5% or more in 37.5% of cases. When $p_{shocks} = 0.5$ the advan-tage of 5% or more is in 25% of cases and when $p_{shocks} = 0.6$ it is in 12.5% of cases. Finally, when $p_{shocks} > 0.6$, need-based rule systems never outperform debt-based rule systems (see Table S6). The general pattern of results fits our earlier find-ings that for lower probabilities of correlated shocks, need-based transfer agents significantly outperform debt-based

Table 3 Small World Networks. This table shows the effect size ρ calculated from the Mann–Whitney U test normalized by the product of sizes of groups (see Tables S3-S5 in Supplementary for associated p-values). Columns represent different values for p_{shocks} while rows represent different network sizes. We can arbitrarily set two thresholds at 0.49 and 0.51, assuming that all values in between are close enough to 0.5 to be considered "as if 0.5" and therefore showing that there is no stochastic dominance of either group. This arbitrary cutoff is confirmed by p-values (see Tables S3-S5 in Supplementary). Values outside that interval (0.49—0.51) are presented in red. All values shown in red are for cases in which there is stochastic dominance of need-based transfers over debt-based transfers; in no cases did debt-based transfers have stochastic dominance over need-based transfers

Small World Networks: ρ values from Mann Whitney U test										
0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
30 0.592	0.553	0.533	0.519	0.526	0.509	0.512	0.505	0.504	0.506	0.5
40 0.577	0.548	0.527	0.519	0.518	0.516	0.512	0.509	0.505	0.504	0.504
50 0.567	0.546	0.528	0.521	0.51	0.511	0.514	0.514	0.499	0.502	0.504
60 0.562	0.536	0.524	0.513	0.515	0.51	0.501	0.499	0.511	0.501	0.503
70 0.567	0.528	0.524	0.518	0.518	0.5	0.502	0.507	0.502	0.501	0.499
80 0.554	0.523	0.525	0.509	0.506	0.513	0.506	0.501	0.507	0.496	0.502
90 0.551	0.526	0.515	0.509	0.512	0.505	0.501	0.505	0.503	0.502	0.502
100 0.555	0.519	0.517	0.506	0.509	0.511	0.511	0.512	0.503	0.495	0.499

transfer agents (see Tables 3 and S3). There was only one combination of parameters where the debt-based strategy outperformed the need-based strategy in small-world networks: 70 agents at an intermediate shock correlation ($p_{shocks}=0.5$). However, this combination of parameters had no effect size and was not statistically significant in our earlier analyses (see Tables 3 and S3).

Regular Networks

In regular networks, when the probability of shocks is low ($p_{shocks} <=0.2$), the need-based rule outperforms the debt-based rule by 5% or more in 58.3% of cases. When the probability of concurrent shocks is intermediate ($0.3 < =pshocks < 0.5$) need-based agents have an advantage of 5% or more in 43.75% of cases. When $p_{shocks}=0.5$, the advantage of 5% or more appears in 25% of cases; when $p_{shocks}=0.6$ they have this advantage in 12.5% of cases. Finally, when $p_{shocks}>0.6$, need-based rule systems never outperform debt-based rule systems (see Table S7). There were no combinations of parameters in which the debt-based agents outperformed the need-based agents in regular networks.

Preferential Attachment Networks

Finally, in preferential attachment networks, when the probability of shocks is low ($p_{shocks} <=0.2$), the need-based rule outperforms the debt-based rule by 5% or more in 16.67% of cases. When the probability of concurrent shocks is intermediate ($0.3 < =p_{shocks} <0.5$) need-based agents have an advantage of 5% or more in 25% of cases. When $p_{shocks}=0.5$, need-based agents have an advantage of 5% or more in 12.5% of cases, and when $p_{shocks}=0.6$ they have an advantage in 25% of cases. Finally, when $p_{shocks}>0.6$, need-based rule systems never outperform debt-based rule systems (see Table S8). Debt-based agents did not outperform the need-based agents under any parameter combinations in preferential attachment networks.

Discussion

We created an agent-based model to investigate how the network topology, the size of the network, and the correlation of shocks affected the viability of need-based and debt-based transfer strategies. We found that agents survived longer in modular preferential attachment networks than in regular and small-world networks. We also found that larger network sizes increased survival, that higher correlations among shocks decreased survival, and that agents following a need-based transfer rule were generally more likely to survive than those following a debt-based transfer strategy. This advantage of need-based over debt-based strategies was especially clear in modular and small networks when correlations among shocks were low.

Although there were conditions in which the need-based and debt-based strategies did equally well (e.g., when shocks were highly correlated), there were no conditions in which the debt-based strategy outperformed the need-based strategy.

Limitations of the Success of Need-Based Over Debt-Based Transfers

Transfers to those in need, often with no expectation of repayment, are common in human risk-pooling systems such as central-place food sharing among foragers and the osotua system of the Maasai (Bird *et al.,* 2002; Cronk *et al.,* 2019). This suggests that need-based transfer systems may have an adaptive advantage over other transfer rules (Cronk & Aktipis, 2021). As we have seen, the need-based sharing rule outperforms the debt-based sharing rule when networks are modular and small and when shocks are not highly correlated. However, the advantage of need-based strategies over debt-based strategies disappears when shocks are highly correlated, and both strategies do equally poorly.

Does the Modularity of Networks Increase their Resilience?

Networks that are more modular tend to be more resilient to perturbations (Ash & Newth, 2007; Bettencourt *et al.,* 2007; Bullmore & Sporns, 2012; Eriksen *et al.,* 2003; Garas *et al.,* 2008; Guimera *et al.,* 2005). Modular networks are typically more resilient against cascading failures. Self-contained or modular components can help to isolate shocks and prevent the cascade of negative effects through the network (Ash & Newth, 2007). However, scale-free networks can sometimes be more vulnerable to targeted attacks than other networks if those attacks are concentrated on more connected nodes (Lenzu & Tedeschi, 2012).

Generally speaking, however, networks that are less modular (e.g., regular networks and small-world networks) are more vulnerable to the effects of shocks. Future work should investigate which characteristics of preferential attachment networks are driving this effect—in particular, whether the modularity of the network is the key factor or whether other network factors drive the effect. In our simulations, preferential attachment networks also have a higher average degree (i.e., the number of connections or edges that nodes have to other nodes) and higher average Eigenvector centrality (i.e., a measure of the influence of a node in a network).

How relevant this finding is to the social networks of Maasai and other pastoralists is unclear. Although we do know that some human social networks are modular (e.g., Newman, 2006), we do not know the structure of real-world risk-pooling networks specifically. Information about such

networks' parameters could be used as the basis for future efforts to create computer simulations of such networks.

Correlated Disasters Strain the Resilience of Resource Transfer Systems

Our finding that correlated disasters lead to much lower survival than uncorrelated ones replicates an earlier model of osotua networks (Hao *et al.,* 2015b) and is similar to that of a model of shocks in financial systems (Steinbacher *et al.,* 2016). The authors of that paper argue that the detrimental impact of systemic shocks comes from the fact that the shocks themselves reduce the wealth of each node of the network in the system at the same time, which makes them more vulnerable to shocks in subsequent periods. Hence, large shocks are likely to be followed by cascading defaults, thereby destabilizing the whole system.

When shocks are highly correlated, the result may be that no transfers occur because no one can afford to help anyone else. Such situations have been known to arise during severe famines, as during the Emutai period among the Maasai mentioned in the introduction. Similarly, in the 1960s, the Ik, a group of former hunter-gatherers in northeastern Uganda, suffered from such a severe famine that an ethnographer present at the time noted a marked lack of sharing, even among close kin (Turnbull, 1972). Although that ethnographer interpreted the lack of sharing as an aspect of their cultural traditions (rather than as a response to their extremely dire circumstances), subsequent work has shown that their culture actually celebrates and encourages sharing and that Ik routinely share with those in need when they are able to do so (Townsend *et al.,* 2020). These findings from the field are consistent with the model results showing that correlated shocks present a unique challenge to overall survival in a network, even when generous sharing rules are in place.

The superiority of need-based transfers over debt-based transfers in these models can be attributed to the simple fact that debt-based agents sever ties with other agents who, particularly in a volatile environment, might actually be helpful to them at some point in the future. Need-based agents, in contrast, do not expect to be repaid and so maintain all their partnerships, thus increasing the likelihood that they will receive help when they need it.

Why Do Debt-Dased Transfers Continue to Exist?

This leads to the question of why need-based and debt-based transfers coexist as they do among the Maasai and in many other societies around the world. We propose that each one is appropriate in specific but quite different

circumstances. When needs arise on a regular, predictable basis, it is possible for people to agree to a balanced exchange of favors: You help me today, I'll help you tomorrow. When such favors are not repaid, it also makes sense to end the relationship and try again with someone else. In these debt-based relationships, the possibility that the relationship will end because of a lack of repayment makes individuals wary about engaging in debt-based interactions with valued partners. It also may be hard to enforce repayment in this kind of situation. For example, Samburu do not engage in esile transactions with affines, brothers, or isotuatin: "you could not argue with them if they don't repay you" (Perlov, 1987:185). But when needs arise unpredictably, it is sensible to simply help those in need so that they will still be around to help you if you yourself are in need at some point in the future.

This is also well illustrated by a pattern of sharing called 'neighboring' that we have observed among ranchers in the American Southwest (Cronk, 2015; Cronk *et al.,* 2019, Cronk *et al.,* 2021). Neighboring has two varieties, one that corresponds with debt-based transfers and another that corresponds with need-based transfers. For help with predictable chores, such as rounding up livestock for branding or marketing, ranchers agree to trade favors in the form of skilled labor, and most ranchers expect such shared labor to be repaid. But when needs arise unpredictably (e.g., due to injuries, illnesses, and deaths), most ranchers provide help to those in need with no expectation of any repayment beyond a similar kindness should they themselves ever suffer from a similarly unpredictable need.

Network Sizes and Pastoralist Survival

In our models, a major determinant of agents' survival was simply the sizes of the networks they were in: agents who happened to be in large networks survived, on average, at higher rates than agents in smaller networks. This may have implications for the survival of pastoralists and pastoralism in the real world, as well. If pastoralist communities are shrinking due to, for example, outmigration and the adoption of other subsistence modes, this could reduce the viability of their risk-pooling networks and threaten the survival of such communities even further. However, this effect might be counterbalanced, at least in part, if support from other economic activities, such as wage labor, enabled them to manage the risks of pastoralism in other ways such as improving veterinary care, buying commercial insurance (e.g., Bertram-Huemmer & Kraehnert, 2018; Takahashi *et al.,* 2018), or simply saving money in anticipation of hard times.

Need-Based Transfers may be Relevant for Disaster Response and Recovery

Our findings may have implications for real-world disaster response. When disasters occur asynchronously in the model, agents survive longer if they use a need-based transfer strategy rather than a debt-based strategy and if networks are larger and more modular. Because it may be difficult in many circumstances to simply create larger or more modular networks, perhaps the most important take-home message is that, when disasters and other negative events arise unpredictably, it may be more adaptive to simply give to those in one's network who are in need if one is able to do so and to do so without any expectation of repayment, rather than to give with the understanding that the relationship will end if the gift is not repaid. Such spontaneous helping networks often do emerge in the aftermath of disasters, with individuals helping strangers without expecting anything in return (Ripley, 2009; Solnit, 2010). For example, after the 1906 earthquake in San Francisco, even traditionally market-driven exchanges, such as food deliveries and transportation, became need-based, with food being distributed and public transportation running for free until after the crisis passed (Solnit, 2010). These examples, combined with the modelling results we report above, suggest that need-based helping systems may be an important part of the human toolkit for surviving disasters.

Glossary

Social Network
Analysis (SNA)   is the process of investigating social structures through the use of networks and graph theory. It characterizes networked structures in terms of nodes (i.e., the entities considered as the single units for the analysis, which may be single individuals, groups of individuals, or different types of actors, such as nations or firms) and the edges, also referred to as links or ties, which represent the dyadic relationships or interactions that connect the nodes.

Regular Network   In graph theory, a regular graph (or network) is a graph where each node has the same number of neighbors. In other words, every node has the same degree

	(i.e., number of connections with other nodes).
Small World Network	A small world network is a network where the typical distance, L, between two randomly chosen nodes (the number of steps required) grows proportionally to the logarithm of the number of nodes N in the network (Watts & Strogatz, 1998). At the same time, the clustering coefficient is not small. In the context of a social network, this results in the small world phenomenon of strangers being linked by a short chain of acquaintances. Many empirical graphs show the small world effect, e.g., social networks, the underlying architecture of the Internet, wikis such as Wikipedia, and gene networks.
Preferential Attachment Network	Preferential attachment is the mechanism used in generating the networks. Intuitively, preferential attachment can be understood if we think in terms of social networks connecting people. Here a link from A to B means that person A "knows" a person B. Heavily linked nodes represent well-known people with lots of relations. When newcomers enter a community, they are more likely to become acquainted with one of those more visible people rather than with a relative unknown. The Barabási–Albert model (Barabási & Albert, 1999) is an algorithm for generating modular random scalefree networks using a preferential attachment mechanism. Several natural and human made systems, including the Internet, citation networks, and some social networks are thought to be approximately scale-free and certainly contain few nodes (called hubs) with unusually high degree as compared to the other nodes of the network.
Degree	The degree of a node in a network is the number of connections or edges that connect the node to other nodes (see Freeman, 1978). An edge is defined as a line segment that connects two nodes.
Modularity	Modularity is one measure of the structure of networks or graphs. It is designed to measure the strength of division of a network into modules (also called groups, clusters or communities; Newman, 2006). Networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules.

Declarations

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