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The economics and evolution of heroic behavior

Daniel FARHAT
Radford University, USA
dfarhat@radford.edu

Abstract. *This study uses a simulation model to explore the causes of 'extreme civil heroism': risking one's life to help a stranger. The model uses a mixture of traditional economic thinking (based on rational self-interest) and human behavioral ecology (based on natural selection). Simulated agents choose between two competing communities (one with heroism and one without) by maximizing expected utility. Which community thrives is observed. Labor productivity, risk tolerance, perspectives on death, emergency response training and accident probability are analyzed as drivers of heroic community success. A preliminary assessment of the model is conducted using data from Eastern Europe. Avenues for future research are described.*

Keywords: heroism, social simulation modeling, altruism, human behavioral ecology.

JEL Classification: B52, D9, D64.

1. Introduction

What makes a hero? Franco, Blau and Zimbardo (2011, p. 101) name four attributes that define a heroic act: (1) it is in service to others in need, (2) it is voluntary, (3) it occurs with recognition of the possible costs and risks, and (4) it occurs without anticipating some external reward. Franco, Blau and Zimbardo (2011, p. 102) go on to categorize heroes by the nature of their actions, their circumstances (physical risk, reputation risk, presence of onlookers, etc.) and their personal characteristics (profession, motivation, etc.). One type of hero in this taxonomy is civil heroes: "civilians who attempt to save others from physical harm or death while knowingly putting their own lives at risk". An extreme form of civil heroism is when the hero tries to save complete strangers. This form of civil heroism is revered, often rewarded with medals/prizes(1) and given attention in the media. Unfortunately, the existence of extreme civil heroism is difficult to explain.

From an economics perspective, a rational agent selects an action only if its expected net gain (benefits minus costs) is the highest among a set of alternative actions. According to the definition of extreme civil heroism, the benefits are negligible. The hero has no personal relationship to the victim and does not expect any sort of social benefit or monetary return when the act is chosen. The definition also implies the potential cost is quite high since the hero may lose their life. The expected net gain of this type of heroism can easily fall below the net gain of by-standing (doing nothing), making extreme civil heroism an unlikely choice for a rational agent.

Extreme civil heroism is also unlikely from the perspective of behavioral ecology. Behavioral ecology assumes behaviors evolve through a process of natural selection where fitter strategies survive and are passed on. Imagine there are two types of individuals: some have 'hero genes' while others have 'by-stander genes'. These behavioral genes may be transmitted through learning or culture. Heroes are behaviorally programmed to always rush in and risk their lives to save victims while by-standers never do; it is 'in their nature'. Heroes will have a higher death rate than by-standers, eroding their survival probability and reducing the likelihood they pass their behavioral traits on to the next generation. Society must reward heroic acts sufficiently and in particular ways to offset the loss in fitness, even if heroes do not expect such benefits when choosing their actions. Becker and Eagly (2004, p. 165) suggest that "increased power, status, and mating opportunities" could have reinforced extreme pro-social behavior in our ancestors (in men, specifically). Other types of rewards, like posthumous reverence, can perhaps support social transmission of heroic culture. However, finding the right balance between risk and reward is tenuous. Heroes will die out quickly the moment the rewards become insufficient.

This study develops a simple simulation model using elements of expected utility maximization and natural selection to see which factors drive the development of heroic communities. In the model presented below, agents choose between two communities: one with heroism and one without. Agents choose the community with the highest expected utility and adopted the associated behavior through cultural transmission. Many parameters related to production, survival, risk-tolerance and demography are included in the model to pinpoint the factors resulting in the growth of heroic communities, thereby explaining the persistence of extreme civil heroism. Note that the model used in this study is individual-based; the actions of individual agents are simulated which result in community-level outcomes. Simulating the growth of communities in this way helps to quickly see model results and identify the effect of changing model parameters.

The remainder of this study consists of a short literature review followed by a description of the model. Parameters are selected and preliminary simulation results are presented along with a discussion on how parameter choices affect the rise of heroic communities. The potential for future research is then discussed. The paper concludes with a summary of findings.

2. Literature of interest

A. Simulation methods and agent-based modeling

The method used in this study asks an artificial agent to choose between two competing communities. One community requires heroic behaviors and the other does not. The agent, who is new to the area, uses reported properties from the two communities to decide which to join. Once the agent joins their selected community, that community's properties are updated for the new population size. The updated properties are used by the next new agent. This approach is inspired by a technique known as agent-based modeling.

Agent-based models [ABMs] are computational simulations where an artificial environment is created and populated with synthetic individuals ('agents'). Each individual agent has unique characteristics, histories, information and objectives. Agents interact with each other and their environment according to prescribed behavioral rules. Individual interactions lead to aggregate patterns which can then be analyzed. In many cases, the observed patterns are 'emergent': they are produced by a complex system but exhibit features which cannot be obviously attributed to a single component in that system.

The key difference between a typical ABM and the simulation method used here is agent interaction. Agents in this model do not interact with others in their community nor do they make other choices once they join a community. Agents are only 'active' when deciding between communities, and this decision is made alone. Agents are 'passive' for the rest of their life and accept what happens to them. Despite this difference, the simulation approach used here does share some of the benefits of a standard ABM.

The benefits associated with ABMs usually connect to realism, flexibility, complexity, explanatory power and the importance of 'bottom-up' generative science. Researchers have more freedom to choose the behaviors of the synthetic agents and the make-up of the artificial environment; the researcher can tailor the model to better suit a real-world setting. The computer records all agent interactions and outcomes at every point of time, forming a complete history. This is useful in developing a full explanation of phenomena. Further, these models allow 'pieces to form the whole'. Instead of looking at a community in the aggregate or from the perspective of a 'representative' individual, the actions of the 'micro' agents come together in intricate ways to form 'macro' patterns. By using a computer simulation approach, albeit a limited one, this study can produce a flexible model structure which incorporates some evolutionary features. Our simulation method is perhaps what you might call 'semi-bottom-up' since the actions of individuals do create aggregate trends, however the actions are limited to a single point in time and agents are not interacting with each other.

Readers interested in agent-based modeling in general can learn more from Macy and Willer (2002), Mathieu, Beaufils and Brandouy (2005), Tesfatsion (2002, 2007), Tesfatsion and Judd (2005) and Pyka and Fagiolo (2007). Readers who want to know more about the skills and techniques needed to create agent-based models are encouraged to read Railsback and Grimm (2012). Readers who would like to delve deeper into the science of agent-based modeling as it relates to deductive and inductive approaches should read Epstein (1999, 2006). A popular software tool used in agent-based modelling is Netlogo (available at ccl.northwestern.edu/netlogo). Netlogo is the program used in this study and contains many demo models that can help researchers understand agent-based modeling techniques.

B. Human behavioral ecology

Human behavioral ecology [HBE] is a paradigm that uses principles from biology and ecology to explain the presence of certain types of human activities and mindsets. The general idea is that people's strategies, choices, norms and perceptions evolve over time to suit their environment. Behaviors are evaluated according to some measure of fitness. More fit strategies proliferate while less fit strategies die out. Mutation is often included to allow better behaviors to emerge. For a general introduction to HBE, interested readers can review Cronk (1991), Mulder and Schacht (2012) or Nettle et al. (2013).

HBE allows for more realism compared to the rational actor paradigm. It can be argued that people are better at following simple rules-of-thumb than solving complex problems. In HBE, prevailing rules change to achieve progress according to a process of learning or adaptation. HBE can help explain why some sub-optimal, old-fashioned or seemingly irrational behaviors persist. However, some authors note that HBE alone might not be enough to completely explain people's behavior. West and Burton-Chellew (2013) recommend a multidisciplinary approach.

C. Altruism and heroism

There is a large literature on altruism in Economics. This literature broadly seeks to explain cooperative or charitable behavior. Simon (1992) introduces readers to key definitions on what it means to exhibit altruism. A common example is the creation of a public good. Individuals in a community invest their personal resources to produce a good that is shared by everyone. There is an opportunity to free-ride: to take a share of the public good without contributing to its production. Rational, self-interested individuals would choose to free-ride and the public good would never be constructed. Analyses of real communities reveal less free-riding than expected. A researcher may attempt to explain this result by looking at reputation effects, reciprocity, social punishments or how benefits to others may appear in a person's utility function.

A portion of the altruism literature ties in to HBE frameworks featuring evolution. Gintis et al. (2003), Doebeli et al. (2004) and Fletcher and Doebeli (2009) introduce new readers to this topic. The general notion is that altruistic behavior becomes a dominant behavior in situations where altruism has better fitness than non-altruism. Natural selection allows altruism to proliferate and other strategies are forced out. Reputation effects, reciprocity and social punishments can be thought of as adding positively to the fitness of altruism or negatively to the fitness of non-altruism, affecting the evolutionary process.

A key distinction in studies on the evolution of altruism is the difference between the fitness of an individual and the fitness of a group. O'Gorman et al. (2008) and Wilson (2015, p.38) note that altruism as an individual behavior may not have the fitness needed to proliferate via natural selection, but communities with some altruistic individuals may. If we evaluate fitness at the community level instead of the individual level, it may be that communities with altruistic individuals outperform communities with no altruism. Communities with altruism would survive natural selection while those without would die out, making the existence of altruism evolutionary-stable. The idea that natural selection occurs on multiple social levels is a key idea used in the model in this study.

Heroism is an extreme form of altruism (see Franco, Blau and Zimbardo, 2011) and is not unique to humans. There is a set of studies relating to the sort of pure heroism discussed here to the insect world. Readers can see the work on 'eusociality' in Ratnieks and Helanterä (2009) and Nowak et al. (2010). Nedelcu et al. (2010) looks at 'altruistic suicide' in single-celled organisms. In both sets of studies, individuals worsen their own reproductive capability or sacrifice themselves for the good of the group. Groups with heroic attributes have better fitness than those without, allowing them to survive natural selection at the community level. The idea of multilevel natural selection is thus connected to heroic actions in the animal world.

3. A one-period economy model of heroic communities

This study is inspired by the literature on agent-based computational modeling, behavioral evolution and extreme altruism. A simple, flexible agent-based-inspired model is developed which looks at community-level attributes to identify the evolutionary paths of groups. Conditions under which heroism survives natural selection can then be explored. The following sub-sections describe the model.

A. The simulation environment

Consider two communities: one with heroism (H) and one without (N). Occasionally, a new agent ('migrant') appears in the environment and must decide where to live. Once the migrant chooses a community, they adopt that community's social norm. The migrant chooses the community with the highest expected utility, U. Utility is a function of consumption and death.

The two communities share some attributes. The number of individuals in each community is denoted by L_H and L_N respectively. Everyone lives for only one period. Each agent supplies 1 unit of labor to production (inelastic labor supply). It is assumed that total production in community (*Y*) is a function of community size (*L*), and the production functions in each community are identical: $Y_H = f[L_H]$ and $Y_N = f[L_N]$. After production has ended but before workers receive their pay, an accident occurs with probability $\theta > 0$. The accident jeopardizes the life of one of the workers. It is assumed that the accident rate is a function of the community size: $\theta_H = g[L_H]$ and $\theta_N = g[L_N]$. Once accidents take their course, the living agents receive an equal share of the produced output. The output is then consumed. Living agents clone themselves before dying. The clone lives their life in the next period remaining in the community of their parent.

The two communities differ in how accidents play out. When an accident occurs in a non-heroic community, a single agent is drawn randomly from the population. This agent is assigned the role of 'victim' and dies with probability $\mu_N > 0$. The probability of being selected as a victim is $\pi_N = 1/L_N$. Since pre-produced output is equally distributed across surviving workers after the accident stage, agents in non-heroic communities will receive one of two pay possibilities depending on if an agent has died or not:

$$y_N = \frac{f[L_N]}{L_N} \quad \text{or} \quad y_N' = \frac{f[L_N]}{L_N - 1}$$

When an accident occurs in a heroic community, a pair of agents is drawn randomly from the population. The first agent is assigned the victim role and the second agent is assigned the role of 'hero'. The hero tries to save the victim, but may fail resulting in the death of both agents. Note that the hero's decision to rush in is automatic and not deliberated; Rand and Epstein (2014) provide some justification for this in their interviews with extreme altruists. The probability of failure is denoted by $\mu_H > 0$. It is assumed that $\mu_H < \mu_N$, making heroism effective. In a population of size L_H, the total number of possible victim-hero pairs[(2)] is equal to $\frac{L_H!}{(L_H-2)!}$. In this set of ordered pairs, each individual is a member of $2(L_H - 1)$ pairs. Therefore, the probability that any individual is a member of the selected pair is $\pi_H = \frac{2(L_H-1)}{L_H/(L_H-2)!} = 2/L_H$.

In heroic communities, the pay possibilities (depending on if a pair has died or not) are:

$$y_H = \frac{f[L_H]}{L_H} \quad \text{or} \quad y_H'' = \frac{f[L_H]}{L_H - 2}$$

Income translates to utility according to the utility function, $u[\,]$. To fully complete the problem, utility in the death state must be incorporated in the problem. Upon their demise, it is assumed that agents receive utility equal to v. No further assumptions or restrictions are placed on v to accommodate the unknown nature of death.

B. Agent decisions

With the information above, the new migrant entering the environment at the start of the period can compute expected utility in the non-heroic community as:

$$U_N = \theta_L\big(\pi_N(\mu_N v + (1-\mu_N)u[y_N]) + (1-\pi_N)(\mu_N u[y_N{}'] + (1-\mu_N)u[y_N])\big) + (1-\theta_L)u[y_N]$$

In the above equation:

L_N = community population with the migrant (assuming the migrant chooses this community);

$\theta_L = g[L_N]$ = probability an accident occurs;

$\pi_N = 1/L_N$ = probability the new agent is selected to be the victim if an accident occurs;

μ_N = death probability for victim with no heroism;

$y_N = \frac{f[L_N]}{L_N}$ = new agent's share of the income (state when no agent has died);

$y'_N = \frac{f[L_N]}{L_N-1}$ = new agent's share of the income (state when 1 of the other agents has died);

$\mu_N v + (1-\mu)u[y_N]$ = the expected payout (utility terms) when the migrant is the selected victim;

$\mu_N u[y'] + (1-\mu_N)u[y_N]$ = the expected payout (utility terms) when the migrant is not the selected victim.

The migrant can compute expected utility from consumption in the heroic community as:

$$U_H = \theta_H\big(\pi_H(\mu_H v + (1-\mu_H)u[y_H]) + (1-\pi_H)(\mu_H u[y_H{}''] + (1-\mu_H)u[y_H])\big) + (1-\theta_H)u[y_H]$$

In the above equation:

L_H = the community population with the migrant (assuming the migrant has chosen this community);

$\theta_H = g[L_H]$ = probability an accident occurs;

$\pi_H = \frac{2(L_H-1)L_H!}{(L_H-2)!}$ = probability the new agent is selected to be the victim if an accident occurs;

μ_H = death probability for victim-hero pair with heroism;

$y_H = \frac{f[L_H]}{L_H}$ = new agent's share of the income (state when no agent has died);

$y''_H = \frac{f[L_H]}{L_H-2}$ = new agent's share of the income (state when a victim-hero pair has died)

$\mu_H v + (1 - \mu_H)u[y_H]$ = the expected payout (utility terms) when the new agent is in the selected victim-hero pair;

$\mu_H u[y_H''] + (1 - \mu_H)u[y_H]$ = the expected payout (utility terms) when the new agent is not in the selected victim-hero pair.

The new agent will select the hero community if $U_H > U_N$. Fundamentally, this decision depends on relative population size (as all model elements are either set parameters or functions of population) and model parameters.

C. Model parameters

Specifying flexible functions for production, utility and accident probability allows us to explore a variety of community attributes. Consider the following:

Cobb-Douglass Production:

$$F[L] = AL^{\alpha} \rightarrow y = AL^{\alpha-1}; y' = \frac{AL^{\alpha}}{L-1}; y'' = \frac{AL^{\alpha}}{L-2}$$

CRRA Utility Function:

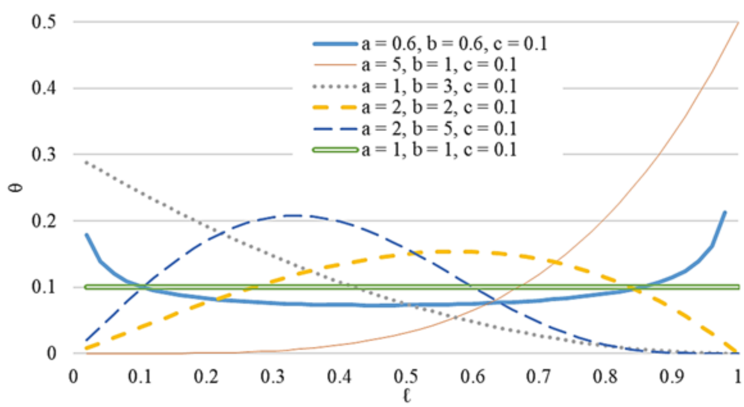
$$u[y] = \frac{y^{\beta}}{\beta} \text{ with } \beta \neq 0$$

Augmented Kumaraswamy Distribution Function with Population Max ($\bar{L}$):

$$\theta = g[L] = abc\ell^{a-1}(1 - \ell^{a})^{b-1} \text{ with } \ell = L/\bar{L}$$

The Cobb-Douglass production function allows us to easily explore increasing, constant and decreasing returns to labor by selecting α appropriately. The CRRA utility function allows us to explore different levels of risk aversion by adjusting the value of β. The augmented Kumaraswamy distribution function is convenient to use as the values of a, b and c produce different relationships between population sizes and the probability of an accident occurring. Figure 1 illustrates possible functions for θ given different calibrations for a, b and c.

Figure 1. *The augmented Kumaraswamy distribution under various calibrations*



We are also free to choose the value of utility in the death state, *v*. This allows us to compare community perceptions of death and the afterlife.

4. Model exploration

To evaluate the drivers of heroism, the model is simulated for 1000 periods at different parameter calibrations. To infer evolutionary advantage, we look at which community grows in population size: the heroism community and/or the non-heroism community. Tables 2A-2C summarize outcomes from single simulations for different calibrated parameters. Column 0 in Table 2A shows the benchmark calibration used here. There are constant returns to labor, risk aversion, no relationship between accident rates and population size, mild efficacy of heroic actions and no utility value prescribed to the death state in the benchmark calibration. Under this calibration, the non-heroism community has evolutionary advantage and dominates (Table 2A-Col 0). Other simulations are compared to this case. A few are chosen to be discussed:

- The efficacy of heroism (lower μ_H). As you might expect, a high level of heroic success (low μ_H) produces an evolutionary advantage for the heroic community (Table 2A-Col 1). This may suggest that communities with knowledge or training on what to do in emergency situations facilitate heroism, allowing the behavior to more easily flourish.
- Decreasing returns to labor (lower α). Decreasing returns to labor leads to simultaneous growth of both the heroic and non-heroic community (Table 2A-Col 2). Neither has an evolutionary advantage. Diminishing returns to labor may attract migrants to lower-population communities, which nullifies the natural selection process regardless of the outcomes of heroic actions.
- Risk aversion (lower β) and risk loving ($\beta > 1$). Risk aversion (Table 2B-Col 4) drives people towards the community with surer outcomes, which in this case is the non-heroic community. However, risk-loving (Table 2B-Col 5) shows that both communities grow. The more tolerant people are of risk, the more likely they will join the heroic community to reap the benefits of altruism despite the increased likelihood of death from having to perform a heroic action.
- Death utility (v). Many economic models about mortality assume that people place a utility value of 0 on the death state. If people think of death either negatively ($v < 0$) or positively ($v > 0$), the actions chosen when their life is at risk is affected. When people have positive perception of the death state, heroic and non-heroic communities co-exist (Table 2B-Col 6). When people have negative perception of the death state, non-heroic communities have the evolutionary advantage.
- Accident rates (a, b, c). Holding all else constant, non-heroic communities have an evolutionary edge when accident likelihood is not strictly increasing with population (Table 2C-Col 8/9/10). Heroic communities are possible if the accident rate increases with population size or density (Table 2C-Col 11).

Table 2A. *Calibration options and summary results*

		0	1	2	3
Parameter		Benchmark	Effective Heroes	Decreasing returns to labor	Increasing returns to labor
A	Production function	1	1	1	1
α	Production function	1	1	0.7	1.2
β	Utility function	0.5	0.5	0.5	0.5
a	Accident probability	0.6	0.6	0.6	0.6
b	Accident probability	0.6	0.6	0.6	0.6
c	Accident probability	0.1	0.1	0.1	0.1
$\bar{L}$	Population max	3000	3000	3000	3000
v	Death utility	0	0	0	0
μ_N	Accidental death probability without heroism	0.40	0.40	0.40	0.40
μ_H	Accidental death probability with heroism	0.20	0.10	0.20	0.20
General Result (Growing Population)		Non-Hero	Hero	Both simultaneous	Non-Hero

Table 2B. *Calibration options and summary results (Cont.)*

		4	5	6	7
Parameter		High Risk Aversion	Risk Loving	Death-Positive Utility	Death-Negative Utility
A	Production function	1	1	1	1
α	Production function	1	1	1	1
β	Utility function	0.1	1.10	0.5	0.5
a	Accident probability	0.6	0.6	0.6	0.6
b	Accident probability	0.6	0.6	0.6	0.6
c	Accident probability	0.1	0.1	0.1	0.1
$\bar{L}$	Population max	3000	3000	3000	3000
v	Death utility	0	0	+5	-5
μ_N	Accidental death probability without heroism	0.40	0.40	0.40	0.40
μ_H	Accidental death probability with heroism	0.20	0.20	0.20	0.20
General Result (Growing Population)		Non-Hero	Both simultaneous	Both simultaneous	Non-Hero

Table 2C. *Calibration options and summary results (Cont.)*

		8	9	10	11
Parameter		Constant Accident Rate	Declining Accident Rate (Safety in Numbers)	Hump-shape Accident Rate	Growing Accident Rate
A	Production function	1	1	1	1
α	Production function	1	1	1	1
β	Utility function	0.5	0.5	0.5	0.5
a	Accident probability	1	1	2	5
b	Accident probability	1	3	5	1
c	Accident probability	0.1	0.1	0.1	0.1
$\bar{L}$	Population max	3000	3000	3000	3000
v	Death utility	0	0	0	0
μ_N	Accidental death probability without heroism	0.40	0.40	0.40	0.40
μ_H	Accidental death probability with heroism	0.20	0.20	0.20	0.20
General Result (Growing Population)		Non-Hero	Non-Hero	Non-Hero	Both simultaneous

The results in Tables 2A-C show that heroism will flourish when it is effective, when people are risk-tolerant, when there is decreasing returns to labor, when people have positive perspectives on death and when accident rates grow with population size. Given these outcomes, the following testable implications can be derived:

- Emergency training should be positively associated with increased presence of heroic communities.
- Diminishing marginal product of labor should be associated with an increased presence of heroic communities.
- Greater risk tolerance should be positively associated with increased presence of heroic communities.
- A strictly positive relationship between population density and accident rates should be associated with increased presence of heroic communities.

The implications above form the basis for future research and policy development. However, two main challenges are present. The first challenge is appropriately identifying ‘heroic communities’. We must be able to distinguish between a community that values heroism and one that does not when testing model implications. We rarely collect data on acts of extreme heroism to use directly. However, a researcher might rely on a proxy. One possible option is to use a survey to measure perspectives on heroic people and/or heroic actions. Survey data is easy to collect, but its value hinges on the assumption that people report their perspectives accurately. Further, we must assume that people who say they value heroism are more likely to engage in heroic acts. An alternative proxy is to use a measure of general altruism. The assumption here is that there is a positive correlation between general altruism and extreme heroism. For example, Falk et al. (2018) provide a national measure of altruism for a group of countries using 2012 data which could be used in a comparative analysis. It should be noted that any significant findings would emphasize the value of general altruism and only imply a community is possibly more heroic.

The second challenge deals with having several important variables changing at the same time. For example, suppose we wanted to test the hypothesis that growing accident rates with population density results in growing heroic communities. Ideally, we would want to compare communities with different levels of populations and accident rates, but similar returns to labor, death perspectives, risk tolerance, etc. to see if the proposed relationship occurs. Finding comparable communities to complete the analysis may be difficult. Alternatively, we can focus on how a community is changing over time. For example, a researcher could conduct a time series analysis of changing heroism sentiments for a single community with changing accident rates, but unchanging returns to labor, death perspectives, and risk tolerance. A requirement for this type of study is having all the necessary variables measured over time.

Testing some of the model’s implications using currently-available data demonstrates this line of inquiry has potential. Suppose the following:

- Assume the national index of altruism in Falk et al. (2018) is a feasible proxy for a country’s appreciation/adoption of extreme civil heroism (i.e. general altruism and heroic behavior are correlated).

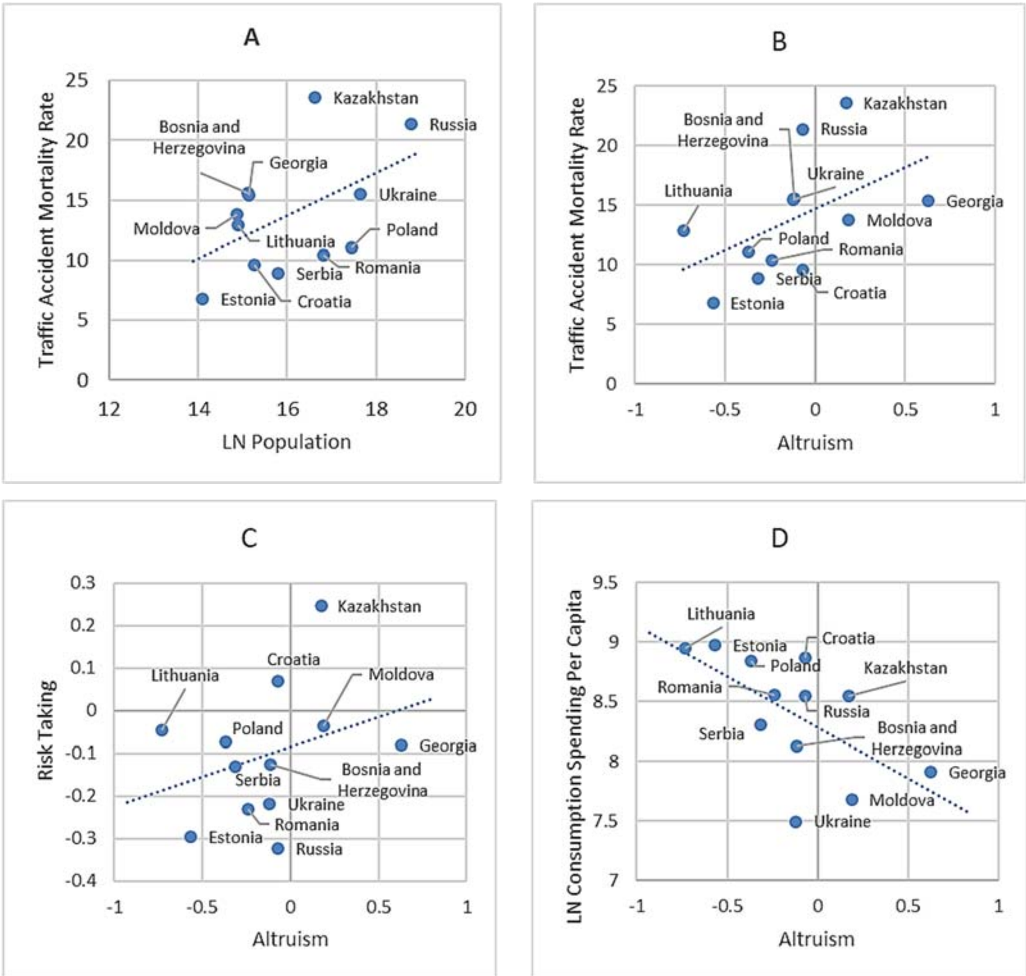
- Falk et al. (2018) also provide an index for risk tolerance, which we assume is correlated with the risk-aversion parameter β.
- The World Development Indicators [WDI] DataBank (2023) from the World Bank provide population levels (L). Data on mortality from road traffic injury (per 100,000 people) is also available in the WDI. Assume this measure is correlated broadly with the general likelihood of having a life-threating accident throughout the economy. These two pieces of data can tell us if accident likelihood increases or decreases with population size.
- The WDI DataBank also provides a measure of consumption spending per capita which we assume is correlated with output per capita and income per capita. The model above is simple, and has no savings or investment. As a result, consumption spending per capita and income per capita (y) are equal in the framework. The agent is ultimately interested in consumption; income is used as a stand-in in the model. We therefore use consumption spending when dealing with real data as an appropriate metric for testing purposes.

We can then analyze a set of countries in the same region using 2012 metrics to suit the data used in the Falk et al. (2018) study. The goal is to see if the relationships we observe in real data are consistent with some calibration of the simulation model.

Given the data available, Eastern Europe[(3)] provides an interesting case study. In this region, we see a positive relationship between population size (LN) and accident probability (see Figure 3A). Accident rates that grow with population size improve the likelihood of heroic behaviors according to the model above (Table 2C-Col 11), and we do observe a positive relationship between altruism and accident rates (Figure 3B). We also observe a positive relationship between altruism and risk tolerance in this region (Figure 3C) which supports model findings (Table 2B-Col 5).

Note that data suggests a negative relationship between consumption spending (LN) and altruism (Figure 3D). The model is capable of replicating this as well if differences in technology (A) or decreasing returns to labor are included. In the model, spending (output) per worker equals $y = AL^{\alpha}/L = AL^{\alpha-1}$. Spending per capita is constant at A under constant returns to labor ($\alpha = 1$). Augmenting technology, A, while keeping constant returns to labor re-scales output without changing the model outcomes. Figure 3D can arise if these Eastern European countries have different technology levels. Spending per capita also rises with α. According to the model results, $\alpha < 1$ supported the development of heroic communities (Table 2A-Col 2). Figure 3D can also occur if $\alpha < 1$ for all countries in the sample, but countries have different levels of α.

Figure 3. *Eastern European analysis*



The Eastern European analysis suggests that a simulation with increasing accident rates, varying levels of risk tolerance, varying levels of production technology and varying levels of diminishing returns to labor would be consistent with the data. This analysis is rough and incomplete, but illustrates promise in this line of research. Different results might occur if we use alternative measures or look at different groups of relatable countries. Further explorations, along with novel additions to the model, can help us better identify the factors allowing heroism to arise in different environments.

5. Conclusion

This study creates a flexible simulation model of pure heroic altruism to analyze the factors affecting the evolutionary path of communities. The model has semi-rational decision-making on behalf of agents who base their choice of community on expected utility.

Changing parameter values and looking at outcomes in sample simulations tells us which community, heroic and/or non-heroic, obtains an evolutionary advantage. In the end, we can infer how returns to labor, risk aversion, population size and death perceptions affect evolutionary pressures. Comparative empirical studies can be relied upon to test these implications (provided data is available).

Extended implications are of particular importance. For example, we may expect economies with rapid technological progress to exhibit production trends that reduce the evolutionary fitness of heroism in the same way that increasing returns to labor does. We may also expect economies with more entrepreneurs to also have more heroics, since both require a larger degree of risk tolerance. We might expect cultural perceptions of death and the afterlife to have significant impacts on people's decisions to help others in an emergency. There may be a significant difference between rural heroics and urban heroics, provided that population density and accident rates are influential. This may change how people see small-town living versus life in a big city. These are all unanswered questions stemming from this line of inquiry that can be investigated further.

Notes

(1) 'Extreme civil heroism' is consistent with the definition of 'hero' used by the Carnegie Hero Fund Commission as noted by Becker and Eagly (2004).

(2) Any agent, j, could be either a victim (first agent) or a hero (second agent). Both possibilities are accounted for by computing the total number of ordered pairs (or permutations). The number of permutations of *n* objects taken *r* at a time equals $\frac{n!}{(n-r)!}$.

(3) Bosnia and Herzegovina, Croatia, Estonia, Georgia, Kazakhstan, Lithuania, Moldova, Poland, Romania, Russia, Serbia and Ukraine.

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