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The Evolutionary Basis of Honor Cultures

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Abstract

Around the globe, people fight for their honor, even if it means sacrificing their lives. This is puzzling from an evolutionary perspective, and little is known about the conditions under which honor cultures evolve. We implemented an agent-based model of honor, and our simulations showed that the reliability of institutions and toughness of the environment are crucial conditions for the evolution of honor cultures. Honor cultures survive when the effectiveness of the authorities is low, even in very tough environments. Moreover, the results show that honor cultures and aggressive cultures are mutually dependent in what resembles a predator-prey relationship described in the renowned Lotka-Volterra model. Both cultures are eliminated when institutions are reliable. These results have implications for understanding conflict throughout the world, where Western-based strategies are exported, often unsuccessfully, to contexts of weak institutional authority wherein honor-based strategies have been critical for survival.

Keywords

cross-cultural differences, honor, aggressive behavior

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Around the globe, people fight for their honor, even if it means sacrificing their lives. Honor cultures vary in their specific codes, but they share one fundamental characteristic: the willingness to retaliate against other people to defend one's reputation, even if doing so is very risky or costly (Nisbett & Cohen, 1996; Peristiany, 1965). This behavior is puzzling from an evolutionary perspective. Indeed, at first glance, the culture of honor would appear to be highly maladaptive, given that individuals prefer the intangible good of preserving their reputations above safety or material gain. However, honor cultures may be highly rational and adaptive in ways that are not fully understood. We predicted that under certain conditions, a good reputation might have more value than safety or material gain. It has been speculated that honor cultures develop in contexts in which resources are scarce and institutions are weak (Nisbett & Cohen, 1996; Shackelford, 2005), yet no research has examined whether these conditions actually allow for the evolution of honor cultures or has examined the relationship of honor cultures to other cultures. In today's world of increasing conflict—which often involves cultures of honor—it is critically important to understand their evolution.

We present one of the first models to simulate the context in which honor cultures evolve, and we present results from simulations run using that model. Our findings show that two simple factors affect the evolution of honor cultures: effectiveness of police and toughness of the environment. We also found that the culture of honor is dependent on the culture of aggression in a way that resembles the dynamics described in the famous Lotka-Volterra mathematical model of biological processes (Hofbauer & Sigmund, 1988), in which the population of predators follows the population of prey in a cyclical way. We show that, far from being irrational, honor cultures are critical for societies under certain conditions because honor cultures can restrain otherwise uncontrolled aggressive behavior.

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Analytic Approach

Psychological research on honor has typically focused on one-shot laboratory and field experiments (Cohen & Nisbett, 1997; Cohen, Nisbett, Bowdle, & Schwarz, 1996; Cross, Uskul, Gerçek-Swing, Alözkan, & Ataka, 2013; Cross, Uskul, Gerçek-Swing, Sunbay, et al., 2013; Leung & Cohen, 2011; Uskul, Cross, Sunbay, Gercek-Swing, & Ataca, 2012; Vandello & Cohen, 2003; Vandello, Cohen, & Ransom, 2008), which have provided important insights into individual-level beliefs and behaviors linked to the construct yet do not examine the dynamics and evolution of honor cultures. Agent-based modeling is ideal complement for this experimental work because it captures the emergence of cultural patterns on the basis of extant situational conditions. Such models have been successfully applied to diverse topics, such as formation of public opinion (A. Nowak, Szamrej, & Latane, 1990), emergence of cooperation (Axelrod, 1984), motivation (Scherbaum & Vancouver, 2010; Vancouver, Weinhardt, & Schmidt, 2010), the self (A. Nowak, Vallacher, Tesser, & Borkowski, 2000), attitudes (Seitz, Hulin, & Hanisch, 2000), race (Schelling, 1971), personality (Reed & Miller, 2002), and group processes (Gray et al., 2014). Building on this research, we show how agent-based models can be fruitfully applied to understand the dynamics of culture (see also Axelrod, 1997; Roos, Gelfand, Nau, & Lun, 2015).

Agent-based models are critical for psychological science because they help to examine emergent dynamics that cannot be captured at the individual level of analysis. Hence, a major goal of agent-based models is to investigate the group- and society-level consequences of individual-level interactions. In systems composed of many interacting individuals, it is often difficult, if not impossible, to predict the emergent group-level consequences that will occur. As Durkheim (1938) noted decades ago, such processes are *emergent* in the sense that the properties of groups and group-level processes are different from the properties and processes of the individuals of which these groups are composed. Despite this complexity, the goal of agent-based models, following in the tradition of dynamical minimalism (A. Nowak, 2004), is to find a very simple mechanism at the individual level that can explain a complex group level phenomenon. For example, in Schelling's (1971) classic model of racial segregation, two types of agents represented different races, ethnicities, and so forth. The two types of agents were initially placed into random locations on a grid, with some squares left empty. The only individual-level assumption made was that individuals become dissatisfied being in the local minority and will accordingly move to a random empty location if the majority of their neighbors are of a different type. This simple rule resulted in the full segregation of agents in a remarkably short period of time and is now a classic in the field of agent-based computational economics.

Agent-based models might seem complicated, but they are actually quite simple. They start with agents (which can represent people) that are assigned different characteristics (individual differences, e.g., opinions and strategies). These agents then interact with other agents on the basis of a priori rules. For example, among other things, agents can influence the opinions of other agents, pass on information, engage in cooperative or competitive behaviors, and punish other agents for their actions. In computer simulations, as in experimental research, we can vary certain situational conditions, such as the amount of resources agents have, the ease of survival, and other external influences. By running the simulation for many steps and allowing agents many chances to interact, we can investigate the final equilibrium state—the state at which the situation stabilizes and there are no further changes. As in Schelling's (1971) model, simulations usually start with a random distribution of variables describing the agents (e.g., attitudes and strategies). Observing how this initially random distribution changes into a well-defined pattern in space, or observing the dynamics of changes of the variables of interest across time, allows the researchers to understand the emergent consequences of the assumptions adopted at the individual level.

We believe agent-based models have great potential for advancing psychological science, as they have advanced economics, political science, and sociology. In our theory, the effectiveness of the police, toughness of the environment, and types of individuals all interact to explain the evolution of honor cultures. We describe how we translated this theory into an agent-based model.

Method: Translating Code Into Simulations of Cultures

Imagine walking down the street when an aggressive person confronts you. You can take a number of different actions. You could use a *rational* strategy and fight back only if you believe you are stronger than the challenger but surrender if you believe you are weaker. You could always fight back when confronted, even if you perceive yourself as weaker, what we refer to as an *honor* strategy. Or you could call the police and ask them to intervene, using what we refer to as an instrumental or *interest*-based strategy. These strategies have their theoretical basis in Weber's (1978) theory of social interaction. Which would you choose? The important question for our model is this: Which of these strategies would be adaptive—or functional—given certain situations?

Our model has an evolutionary basis in that it examines the functionality, or adaptive value, of these strategies given distinct environmental conditions. In evolutionary models, each agent is characterized as having a certain amount of fitness depending on the amount of resources possessed by the agent. In the course of a simulation, the

interactions between agents change the amount of resources that agents have. And in the course of a simulation, *selection* occurs; that is, agents who have low fitness are eliminated. The remaining agents have offspring, with characteristics that are either a perfect or an imperfect copy (i.e., sometimes there are random mutations) of the characteristic (i.e., the strategy) of their parents. By running the simulation for generations and having repeated interactions among the agents with different strategies, we can see which agents do the best—that is, which strategy ultimately predominates in the population? The final percentage of the agents with different types of characteristics is a measure of the functionality of the individual characteristics; the higher the percentage of individuals with a particular characteristic, the higher the functionality of the characteristic.

Accordingly, our honor-evolution model follows an evolutionary framework (Bentley, Hahn, & Shennan, 2004; Bentley, Ormerod, & Batty, 2011; Simon, 1955). The simulation begins with each of the four strategies (aggressive, rational, honor, and interest) having equal representation (25% of the population). Over the course of the simulations, agents have many interactions through which their fitness changes, and their fitness determines whether they survive or are eliminated. The number of individuals representing each strategy in the long run is used as a measure of the functionality of the strategy. Key aspects of the model are described below (for all of the rules of the simulation, see Supplemental Material available online).

How interaction partners were determined

The model was implemented as a set of N agents that interact on a *small-world network* (Watts & Strogatz, 1998) with symmetric connections based on the topology of a 2-D lattice. Such a network structure resembles the structure of connections in the real world, where individuals know most of their neighbors in the social space but also know some distant individuals (Granovetter, 1973; Watts & Strogatz, 1998). To construct such networks, we placed agents in a cell within a square grid of 100 rows and 100 columns. Local connections were generated by connecting the agent through bidirectional links to the 48 neighbors located not farther away than 3 rows and columns. In addition, random connections ($N/2$) were added, irrespective of distance; on the average, each agent had one connection to a random neighbor.

Agent characteristics

As noted, each agent is assigned an action strategy at the beginning of the simulation: the aggressive strategy (i.e., attack agents perceived as weaker), the honor strategy (i.e., always fight back when confronted, even if one is weaker), the interest strategy (i.e., call the police when confronted, corresponding to the people found in what Leung and Cohen (2011) refer to as *dignity cultures*), and the rational strategy (i.e., fight back when one is stronger but surrender when one is weaker).

In addition to their specific action strategy, all agents have a certain degree of *strength*, which corresponds to the amount of resources they have. Strength can be interpreted as the amount of energy that one has to fight (i.e., a life force). Strength is one of the crucial variables that change as a result of interactions. If strength falls below a specified limit, the agent dies. In evolutionary terms, strength is a measure of fitness and it is the basis for selection. Maximum strength is an individual difference variable between 0 and 1, drawn randomly from a semi-normal distribution for each agent.[1] The initial strength is a random number higher than half the agent's maximum strength but lower than the agent's maximum strength. The relative strength between agents determines the results of a confrontation. Both agents engaged in a fight lose strength because fights are costly to physical resources, but the defeated agent loses more strength. Strength is also lost as the result of the intervention of authorities: The perpetrating agent loses strength if the police arrive and the targeted agent loses strength if the police do not arrive. Strength is slightly augmented at the end of each step of the simulations; this mechanism can be understood as recovery from the harm inflicted by confrontation.

Agents also have a certain degree of *reputation*. Reputation corresponds to the perceived strength of the agent (i.e., the perceived likelihood that the person will stand up to a challenge and win the confrontation by his or her own actions). Note that a person who does not stand up to a fight (i.e., who gives up or calls the police) cannot win a confrontation by his or her own actions. Accordingly, this characteristic reflects the likelihood that a challenged agent will decide to fight. All the decisions regarding whether to attack and how to respond when challenged are based on reputation. Reputation is gained by challenging other agents, by taking on a fight when challenged, and by winning a fight. It is lost by giving up when challenged, by calling authorities when challenged (indicating one will not fight), and by losing a fight. Only reputation (and not strength) is known by all of the agents. The higher an agent's reputation, the smaller the probability it will be confronted. Initially, reputation values are equal to the agent's initial strength value, but they are updated after every interaction depending on the behavior of an agent and its consequences. Note that reputation can reach values higher than actual strength.

Agent interactions and their consequences

We use Monte Carlo dynamics, in which an agent is randomly chosen and then an interaction partner is randomly chosen from among connected agents. All of the interactions between agents in the model potentially start with a challenge, which are usually initiated by the aggressive agent, but there is a small probability that a challenge will be initiated by the honor agent. In response to a challenge, the target agent can choose to fight, to give up, or to call the police. All of these actions have consequences for changes in reputation and strength as discussed below.

Fighting. If the agent decides to challenge and the response of the target is to fight, the outcome of the fight is stochastically decided by the ratio of the strengths of the challenging agent and the targeted agent. Winning the confrontation decreases strength by a random value of medium expected magnitude, signifying that the fight is costly. However, losing the confrontation decreases the strength by a random number of even higher expected value. If the targeted agent wins the confrontation, the agent gains considerable reputation. This is because when an agent with a lower reputation wins the fight, this is perceived as an unexpected, courageous act and thus increases the reputation of the target of aggression. If the challenger wins the confrontation, it also gains reputation, but the reputation gain is considerably smaller, because the victory of the challenger is the expected outcome. If the challenger loses the fight, however, its reputation is decreased. Finally, if the target loses the fight, its reputation is moderately increased, because enduring a fight from a stronger aggressor is a sign of courage.

Giving up. If the agent decides to challenge and the response of the target is to give up, the challenger's reputation increases more than it would have if the challenger had won the fight, and the challenged agent loses the same amount of reputation as the challenger gains. The large increase in the reputation of the challenger in this case reflects the fact that an immediate surrender in the face of a confrontation is a strong indication of the challenger's power. A targeted agent that gives up also loses some strength, but not nearly as much as a targeted agent that fights and loses. The loss of strength in this case reflects a loss of resources from being the target of abuse. The strength of the challenging agent does not change because there was no fight. Thus, for the challenging agent, the best outcome in terms of both reputation and strength is when the target gives up.

Calling the police. If a targeted agent calls the authorities and the authorities react effectively, the challenging agent loses the same amount of reputation as if it had lost the fight but loses even more strength than it would have if it had lost. That is, strength is decreased by a random number with the highest expected value of all the conditions. This assumption reflects the fact that police interventions are usually more consequential than lost fights. At the same time, the targeted agent that calls the police loses more reputation than if it had given up because it signals that it will not fight (i.e., it cannot win by its own actions). This loss is motivated by the observation that deferring to authorities is treated as a sign that one will never fight when provoked (hence, losing the reputation to fight). If the police do not arrive, the challenging agent gains even more reputation than if the targeted agent gives up. The reputation of the agent that called the authorities is strongly decreased, and its strength is reduced by a high random number. The strength of the challenger is not affected, because the target did not fight.

Manipulation of the environment

In computer simulations, as in experimental research, we can vary certain situational conditions. To explore the conditions under which honor cultures are functional, we manipulated two aspects of the agents' environment. The effectiveness of the authorities (e.g., police) was defined as the probability of effective intervention when authorities are called. Values ranged from 0% to 100% in steps of 1%. There are regions and situations in the real world in which there are no effective authorities, so it was assumed that 0% effectiveness of authorities could represent existing conditions. Practically speaking, the authorities are never effective 100% of the time; accordingly, 90% effectiveness is the realistic upper limit for interpretation.

The toughness of the environment was operationalized as the percentage of maximum strength that is needed for survival; values ranged from 5% (mild) to 60% (very tough), in steps of 1%. We started from 5% toughness, reasoning that all humans need some resources to survive, so starting from 0% would correspond to conditions that do not exist. We used empirical data on newborns' survival to adulthood to determine a realistic value for the maximum toughness of the environment. In particular, United Nations data (Populationpyramid.net, 2012; U.N. Inter-agency Group for Child Mortality Estimation, 2014) show that in countries with the weakest health-care systems, up to 50% of people born die before they reach adulthood. Accordingly, we assumed that the minimum value of survival is approximately 50%.

In the simulations, strength is randomly assigned for each agent at the beginning of simulations. The agents

whose strength is lower than the threshold representing the toughness of environment are eliminated at the first step in simulations. This can be interpreted as mortality before reaching adulthood. Given that the mean and the median of maximum strength in a population is 50%, the actual strength is a random number from a flat distribution between half of the maximum strength and the maximum strength. Accordingly, the expected value is at 75% of the maximum strength (which would be 37% for a flat distribution). Because the distribution of maximum strength is normal, the expected median of the distribution of strength is somewhat higher than 37%. Assuming the value of environmental toughness at 40% roughly corresponds to the toughest observed environments in modern times. For the purposes of the simulations, we also compute values of up to 60%, assuming that historically, toughness (e.g., mortality rate) was even higher.

All combination of these values creates an experimental design of 100 (values of police effectiveness) by 55 (values of toughness of the environment), totaling 5,500 cells. For each combination of the independent variables (cell) we ran 10 simulations, so in the main simulation experiment, we ran 55,000 simulations. Each simulation was run for 50,000 steps. In each step, on the average, each agent is given one chance to interact.

Selection processes

There are two mechanisms by which agents are eliminated: selection and natural aging. Selection results from exhausting resources. If the strength of the agent falls below the selection criteria, it is eliminated. Elimination by aging is independent of the resources and occurs randomly. There is a large probability that when an agent is eliminated, it is replaced by a new agent with a strategy randomly chosen from one of its contacts; there is a very small probability that the replacement will be an agent with a strategy chosen randomly from the initial distribution. This mechanism can reintroduce, in very small numbers, the strategies that have been eliminated in the course of dynamics. It corresponds to the diffusion of the cultures, and its function is to prevent a culture from being irreversibly eliminated from a simulation. It also can be interpreted in evolutionary terms as a mutation of a strategy. At the end of a simulation step, each agent's strength is increased by 0.5%, which is interpreted as recovery.

Controls

Agent-based models, like experiments, need to carefully control different factors to make sure they do not unduly influence the results. We conducted many additional simulations that serve as controls or robustness checks. To show the generalizability of our model, we present results for the model without reputation, with different parameter values, with different values for aggression and regeneration, and even with changes to the small-world network on which the agents interact. All results show the robustness of the model (see Results and the Supplemental Material).

Results

We explored how the variations of police effectiveness and environmental toughness influenced the final percentages of agents representing the four strategies after the simulation reached its asymptotic state, which is the time at which the system achieved its final state or pattern of dynamics (i.e., in our model, at 20,000 steps) and was not dependent on the initial conditions of the model. To provide reliable statistics, we then collected data to capture several repeated cycles (usually at least seven) over the next 30,000 steps. The data presented reflect the averages from 20,000 to 50,000 steps of 10 simulations. Each entry represents the averaged percentage of the four strategies in each cell of the design. We now turn to the results regarding when honor strategies are functional and how they relate to the other strategies in different environmental conditions.

When are honor strategies functional?

Figure 1 shows survival for each strategy. Honor agents survived when the effectiveness of the authorities was low, even in very tough environments. If the effectiveness of authorities was greater than 50%, honor agents were drastically reduced and existed only in very small numbers, even in mild environments. Figure 2 depicts the popularity of all strategies on a 2-D graph with colors. It illustrates an emergent phenomenon in which the honor and the aggressive agents survived in identical conditions, mainly when the effectiveness of the authorities was low. In contrast, when the effectiveness of authorities was high, neither the honor nor the aggressive agents could survive in large numbers; they were replaced by interest and rational agents, even in very mild environments.

What are the emergent dynamics between the agents' strategies?

Figure 3 shows percentages of four types of agents over time with environmental toughness set at 25% and effectiveness of authorities set at 5%. The dynamics of the relationship between the aggressive and the honor agents is based on a single simulation run in which the effectiveness of police was low. The popularity of the strategies is

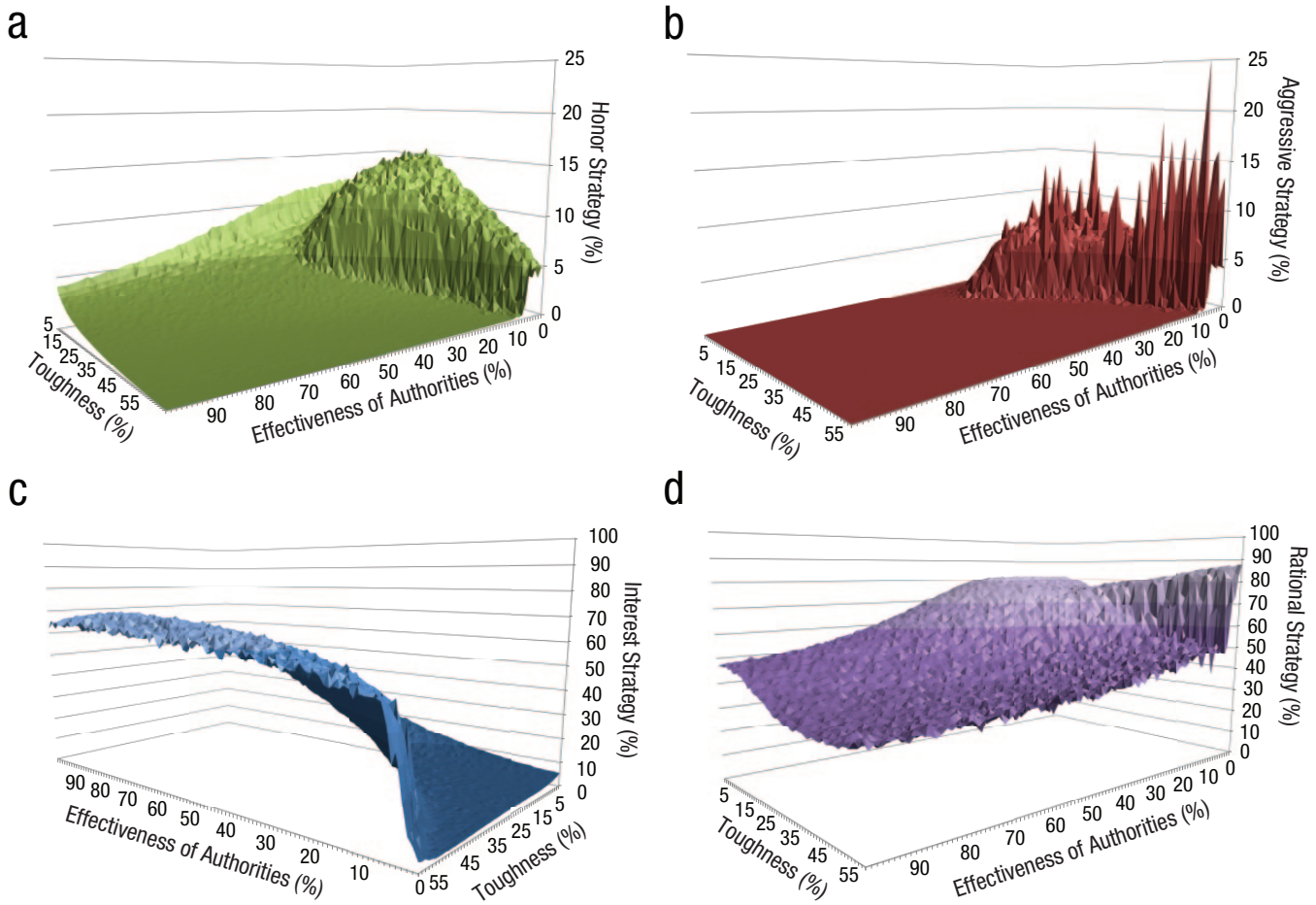

Fig. 1. Final percentage of agents for each strategy. The percentages of agents using the (a) honor, (b) aggressive, (c) interest, and (d) rational strategies are graphed as a function of effectiveness of authorities and toughness of the environment.

displayed as a function of time measured in simulation steps. This figure illustrates a phenomenon in which the popularity of honor agents follows the popularity of aggressive agents. Figure 3 presents a clear oscillatory pattern in which the growth of aggressive agents paved the way for the development and growth of the honor agents. Once the honor agents gained in popularity and eliminated the aggressive agents, the rational agents began to gain in power, eventually eliminating the honor agents. With few honor agents, however, the aggressive agents began to grow, and the cycle continued. Because of the low effectiveness of authorities, the interest agents never reached high power in this scenario.

A spatial representation of these dynamics can be found in Figure 4, which represents the time frame in the dotted oval in Figure 3. In this figure, each agent is represented as a colored dot. At the onset of this time period, aggressive agents (Fig. 4a) began to form a cluster in the upper left quadrant. This cluster grew, and two additional clusters of aggressive agents appeared (Fig. 4b). Eventually, aggressive agents started to dominate the space, but small clusters of honor agents (Fig. 4c) began to form on their borders. The honor agents eventually successfully invaded the areas occupied by the aggressive agents (Fig. 4d). But as the honor agents almost completely eliminated the aggressive agents, pockets of the rational agents (Fig. 4e) began to grow. Rational agents subsequently replaced most of the honor agents, and the interest agents increased their presence. In the presence of few honor agents, a new cluster of the aggressive agents appeared in the lower left, closing the cycle of cultural dynamics (Fig. 4f).

What happens to the population if honor agents are not present?

We ran an additional simulation in which we removed the honor agents from the model. This enabled us to see which of the other strategies dominated and to illustrate the functional role of the honor agents in the system.

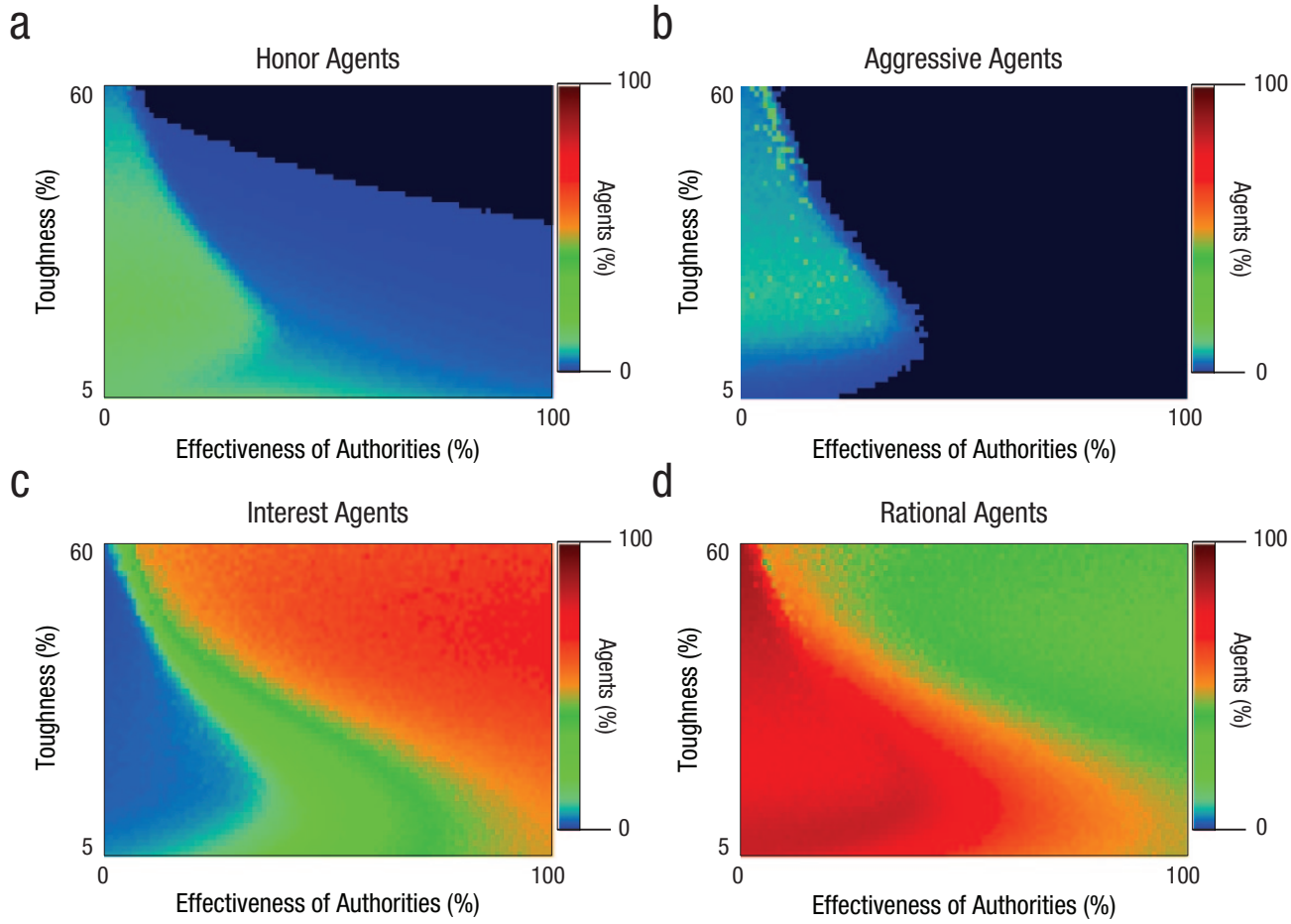

Fig. 2. Visual representation of the interdependence of the four strategies. The color coding represents the percentage of each culture as a function of effectiveness of the authorities and toughness of the environment. Results are shown separately for the (a) honor, (b) aggressive, (c) interest, and (d) rational strategies.

Figure 5a shows how the percentages of the four agent strategies changed over time, from the beginning of the simulation, with the honor agents absent. Figure 5b shows a comparison of the three agent strategies. The figure shows that without the presence of the honor agents, only the aggressive agents survived when the effectiveness of authorities was weak. When the effectiveness of authorities was relatively higher, the aggressive agents are eliminated, and only interest and rational agents remained. In sum, in conditions of low institutional authority, honor agents were critical to stopping the aggressive agents from proliferating.

Why can honor agents control aggressive agents in conditions of weak authority?

The results of the simulations suggest that the culture of honor's willingness to protect its reputation at all costs allowed it to prevail over the culture of aggression. The honor agents' high reputation for fighting could ward off attacks from the aggressive agents. This gave honor agents time to gain strength. Ultimately, when honor agents had high reputation, they had more strength, on average, and could eliminate the aggressive agents. To directly check the assumption that reputation is critically important for the survival of the culture of honor, we ran simulations in which the reputation of honor agents did not change as a consequence of behaviors and instead remained at the initial level (Fig. 6). When reputation was fixed after birth, honor agents were essentially eliminated when the effectiveness of authorities was low, and the aggressive cultures took over the population. The results show that the capacity to attain high reputation was critically important for the culture of honor (for the importance of reputation in the evolution of human societies, see also M. A. Nowak & Sigmund, 1998). Without reputation, honor agents were unable to survive in any condition.

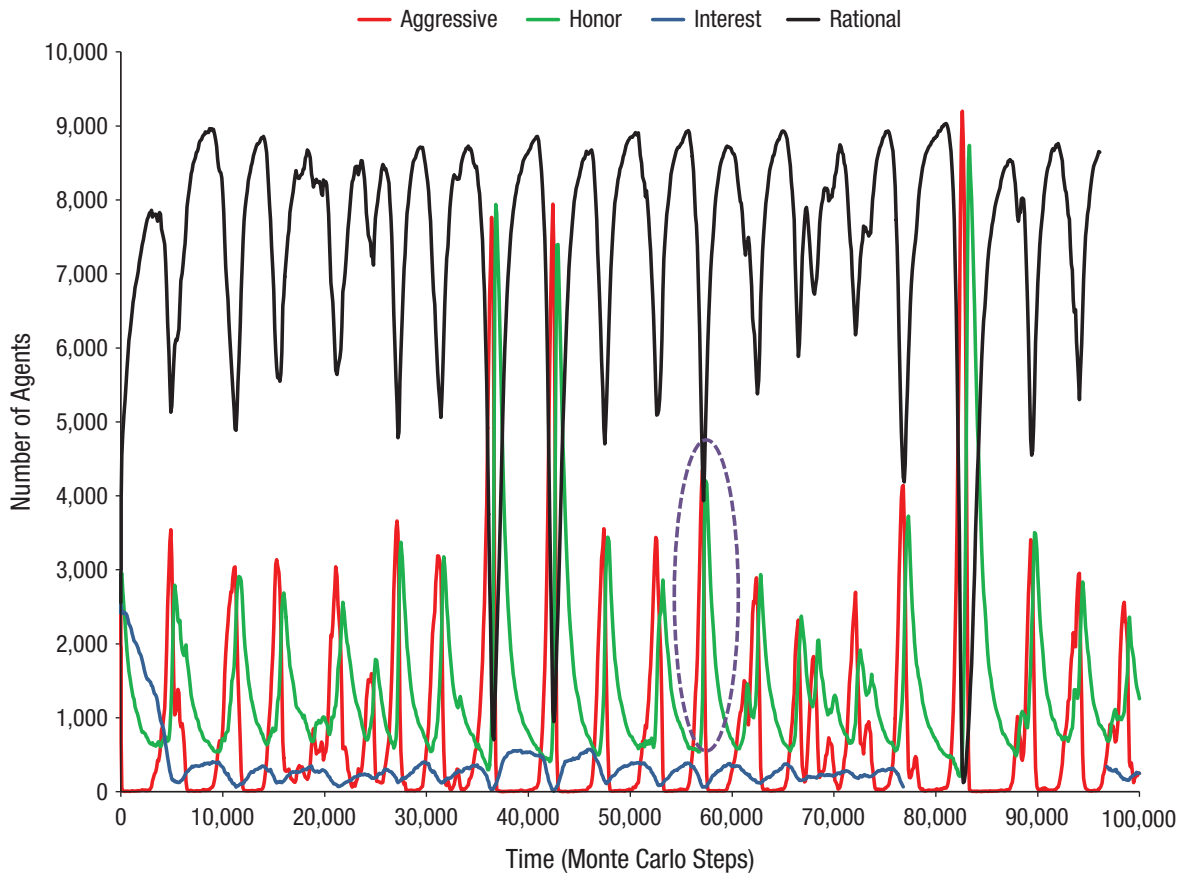

Fig. 3. Time series illustrating the dynamics between honor agents and aggressive agents. The number of agents is plotted as a function of time for the four types of agents. Environmental toughness was set at 25%, and effectiveness of authorities was set at 5%. The area in the dashed ellipse is examined in greater detail in Figure 4.

The Supplemental Material provides numerous additional simulations and robustness checks. The results are robust even when the numerous parameters of the model are changed. In the Supplemental Material, we also provide some empirical data showing that honor cultures indeed thrive when institutions are perceived as weak: Nations with higher honor scores (as measured by the percentage of honor talk in their constitutions; Gelfand et al., 2015) had lower confidence in the police and the justice system as reported in the World Value Survey and the European Social Survey.

Discussion

The viability of honor cultures, in which individuals retaliate against other people to defend their reputation even if it is very costly, has been an evolutionary puzzle. We show precisely why and when honor cultures are adaptive. Results indicated that honor agents were effective in the presence of aggressive agents when the authorities were weak, even in very harsh environments. In this respect, the function of the honor agents was to control the spread of the aggressive agents in contexts of weak institutions. Indeed, our simulations show that without honor agents, aggressive agents would completely dominate and obliterate interest and rational agents if the police are ineffective. The results also illustrate why honor agents can control aggressive agents in these circumstances: Honor agents' reputation for never yielding to pressure prevents attacks from aggressive agents, which enables the honor agents to gain high strength and to ultimately eliminate the aggressive agents.

The results illustrate an emergent relationship of mutual coexistence between aggressive cultures, honor cultures, and rational cultures in environments of low institutional authority. When the authorities were weak, the aggressive agents wiped out the rational and interest agents. The honor agents, by winning some confrontations with the aggressive agents, reclaimed the space previously occupied by the rational and the interest agents and eventually eliminated the aggressive agents. However, in the absence of the aggressive agents, the honor agents were less functional, and the rational agents subsequently replaced most of the honor agents. Ultimately, when

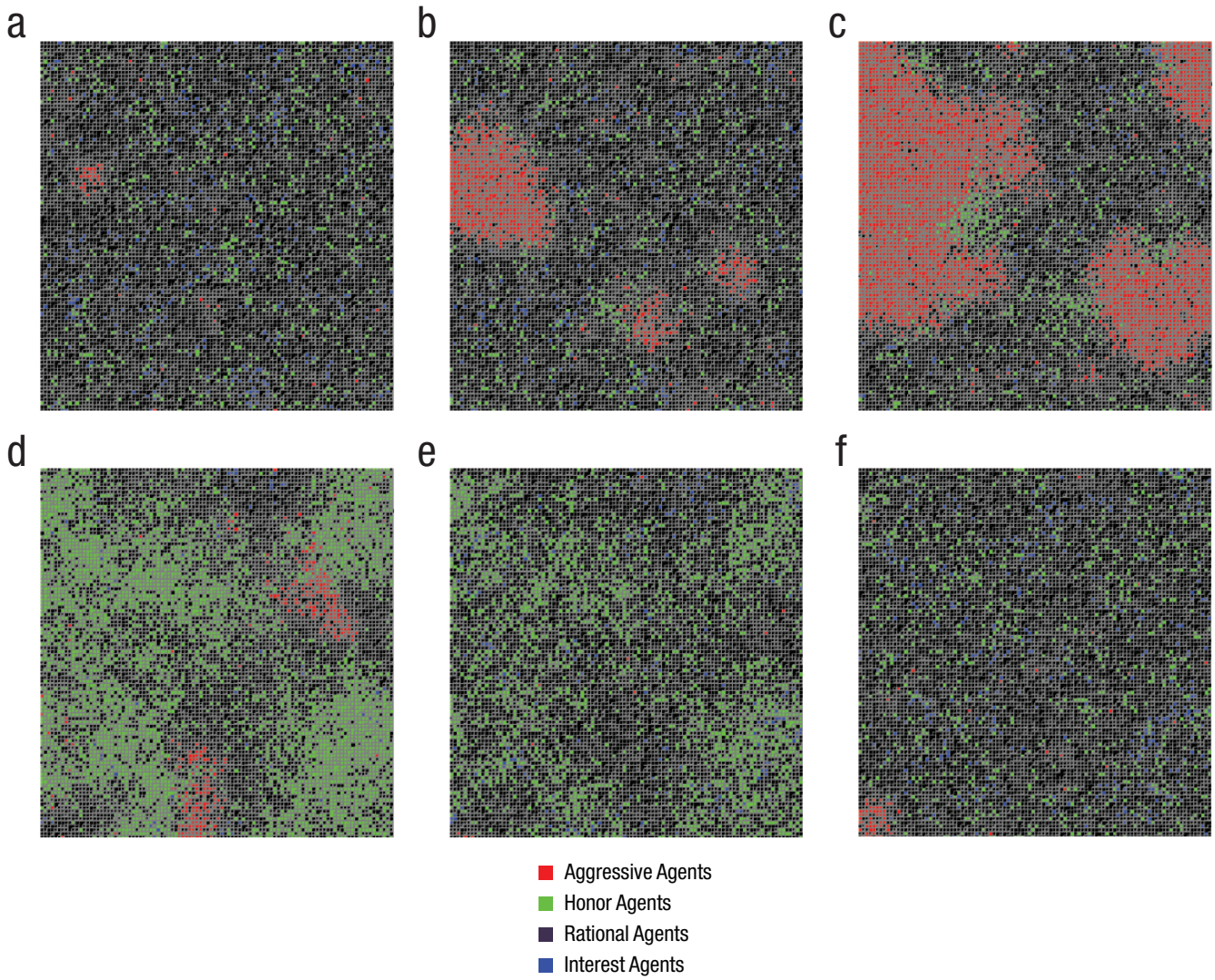

Fig. 4. Longitudinal dynamics of the strategies. The time period covered by the six panels is indicated by the dashed ellipse in Figure 3. Each colored dot represents a single agent. In the simulation illustrated here, environmental toughness was set at 25%, and effectiveness of authorities was set at 5%.

there were few honor agents, a new cluster of the aggressive agents developed that defeated the rational agents, paving the way for the emergence and functionality of the honor agents, and the cycle continued.

The relation between the honor and aggressive agents resembles the Lotka-Volterra predator-prey dynamic, one of the best-known mathematical models of biological processes (Hofbauer & Sigmund, 1988). It describes how the numbers of two species—predator and prey (e.g., foxes and rabbits)—change over time. In particular, the model shows how the population size of the two species resembles two sinusoidal waves, in which the population of the predators follows the population of prey. The dynamics of the model is cyclical: With a small number of predators present, the population of prey grows as it consumes food and has offspring. The growing population of prey presents a growing source of food for the predators, so the growth of the population of the predators follows the growth of the prey. As the number of predators grows, the number of prey starts to decline, which in turn, leads to the decline in the population of the predators. With a small number of predators, the population of prey starts to grow again so the cycle repeats itself. The Lotka-Volterra model has been applied to understand the economy (e.g., Desai & Ormerod, 1998; Goodwin, 1967), crime (e.g., A. Nowak & Lewenstein, 1994), and cooperation (Axelrod, 1984), among other phenomena. To our knowledge, the current study is the first to show that this model characterizes cultural dynamics.

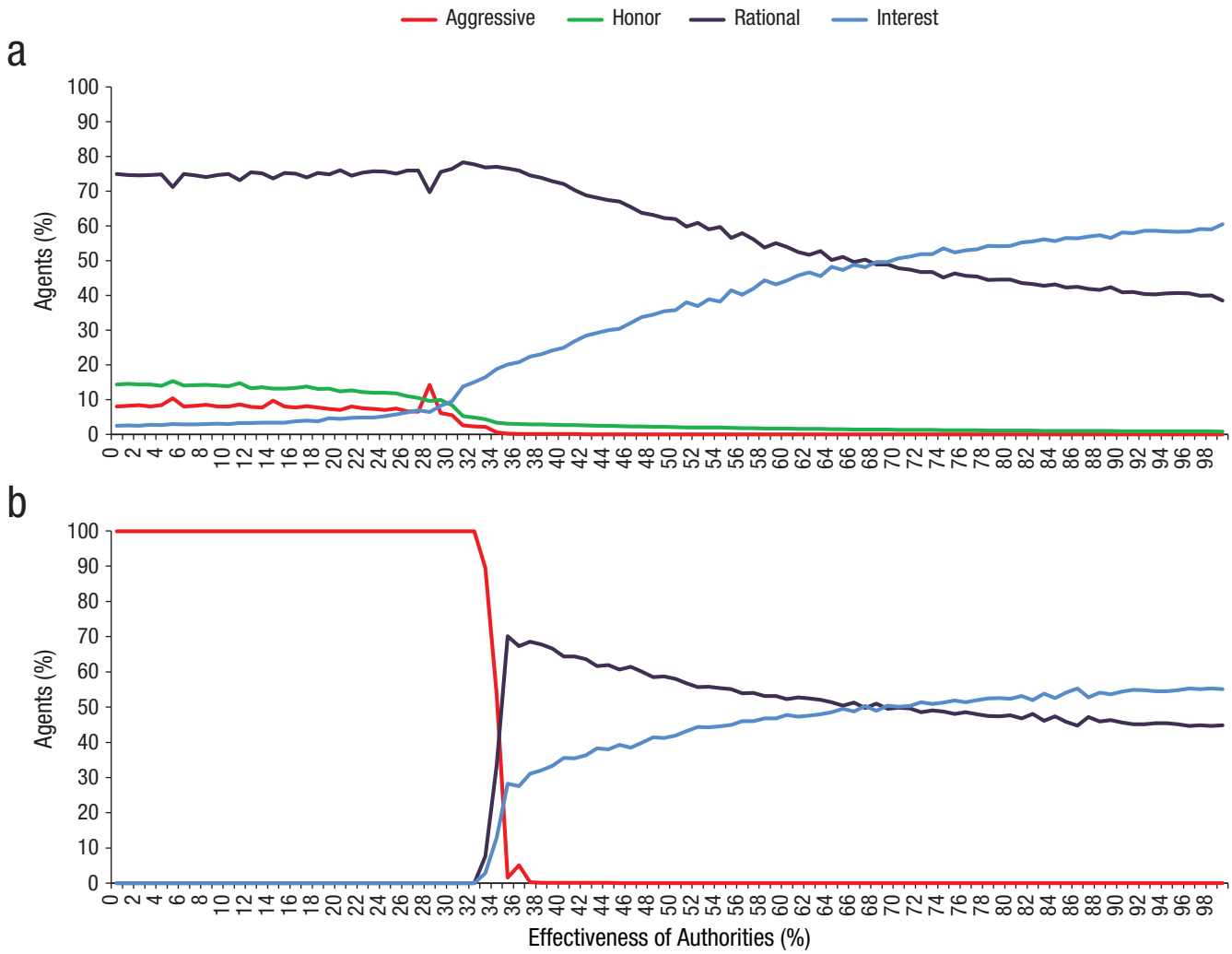

Fig. 5. Comparison of popularity of the different types of agents. The percentage of each type of agent is graphed as a function of the effectiveness of the authorities (a) with and (b) without honor agents present in the model.

Interesting effects also emerged in environments of strong institutional authority: Honor and aggressive agents were dramatically reduced and dominated by interest and rational agents. This effect confirms both the dependence of interest agents on strong institutional authority and the dependence of honor agents on the presence of aggressive agents. It also supports the notion that honor cultures are tied to the importance of reputation, and when reputation has no utility as a shield against aggression (because of the presence of adequate institutional authority), a culture of honor is not functional.

More generally, the simulations illustrate that two systems can provide a sustainable, but highly distinct, way to control aggressive cultures: an honor-aggressive system or a rational-interest system. The strength of the state is the critical element dictating which of these systems is most effective. Above all, the simulations showed that understanding of the evolutionary basis of honor cultures requires considering not only the strength of institutions and toughness of the environment but also the interactions between all of the cultures of the society.

The model also shows why rational versus "devoted" actors (Atran, Axelrod, & Davis, 2007), which are similar to rational and honor agents in our model, respectively, thrive in very different environments and, hence, why it is difficult, if not impossible, to export strategies of one culture to another without changing the larger institutional environment. This has implications for conflict throughout the world: Western rational and interest-based strategies are exported—often unsuccessfully—to contexts of weak institutional authority in which reputation and honor-based strategies have been critical for survival. This research shows that unless changes are made to strengthen institutions in such contexts, rational and interest-based strategies will fail, which is an important policy implication derived from the model.

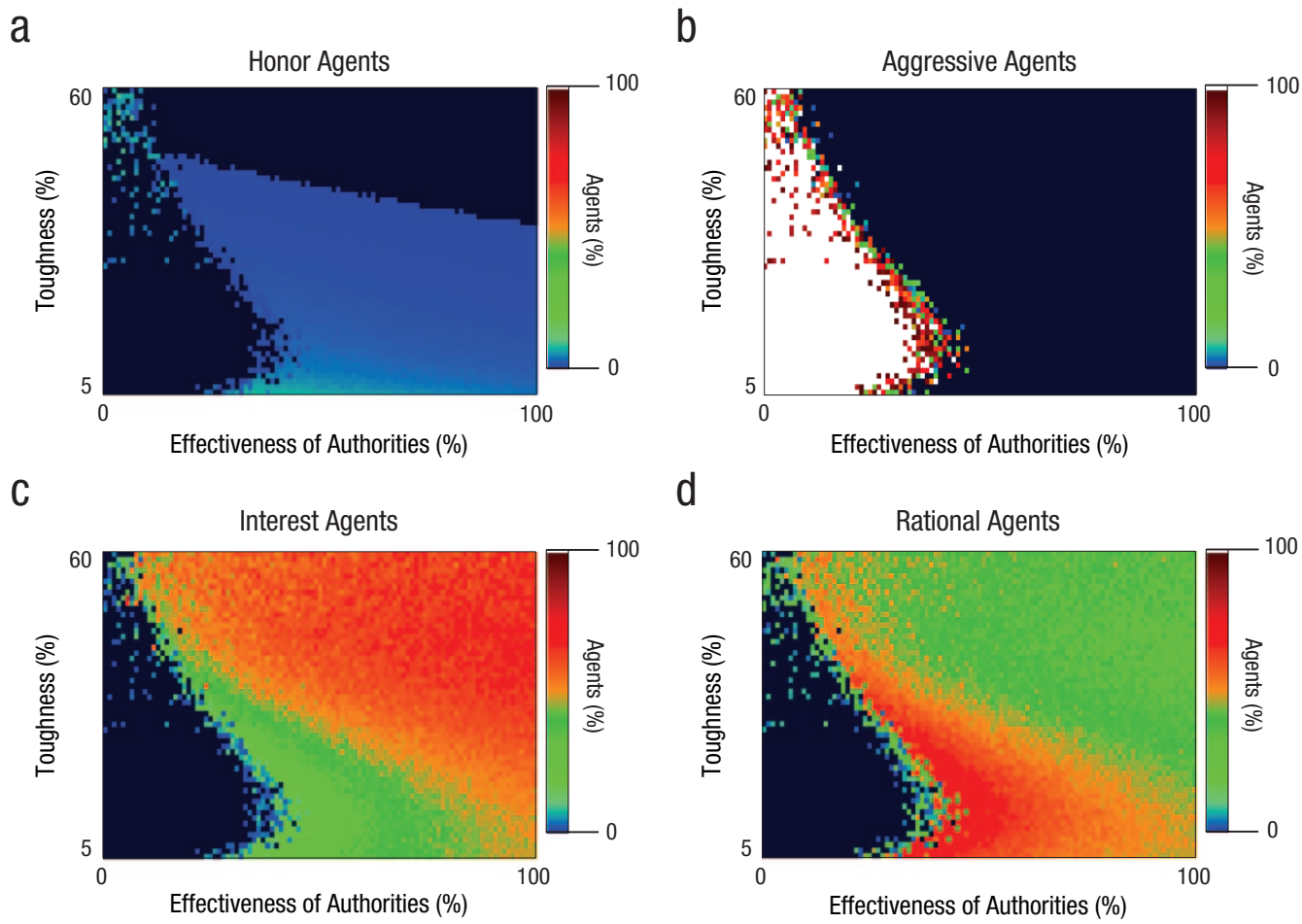

Fig. 6. Results of simulations in which reputation was fixed after birth. The color coding represents the percentage of each culture as a function of effectiveness of the authorities and toughness of the environment. Results are shown separately for the (a) honor, (b) aggressive, (c) interest, and (d) rational strategies. White indicates a ratio of approximately 100%, and the darkest blue indicates a ratio of approximately 0%.

In conclusion, this research shows the promise of agent-based modeling for illustrating cultural dynamics. Culture is an emergent phenomenon; it is created, maintained, transmitted, and changed in individual interactions. Yet at the same time, culture strongly influences individual behaviors and shapes human interactions. Because of the complexity of the mutual influences within and between the levels of social systems, it is often impossible to understand how properties and interactions at the individual level result in dynamics of culture at the societal level. Agent-based models are ideally suited to investigate how cultural dynamics emerge from complex feedback loops involving individual strategies, social interactions, and features of the environment. With real societies, we cannot manipulate experimental conditions at the population level and observe how a culture evolves for hundreds of generations, yet computer simulations enable us to do so (see also Axelrod, 1997). In sum, understanding the dynamics of cultures requires a combination of different research tools, and agent-based models are proving to be an important part of that cultural toolkit.

Author Contributions

A. Nowak, M. J. Gelfand, W. Borkowski, D. Cohen, and I. Hernandez developed the theory. W. Borkowski wrote the simulation code. A. Nowak and W. Borkowski ran simulations. A. Nowak, M. J. Gelfand, W. Borkowski, D. Cohen, and I. Hernandez provided interpretations. A. Nowak, M. J. Gelfand, and W. Borkowski wrote the manuscript.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Note

1. The seminormal distribution was obtained by randomly drawing several numbers from the flat random distribution and taking their mean value. A seminormal distribution is bell-shaped, like a normal distribution; however, the random numbers that are generated from a seminormal distribution are bounded on both the low and high values.

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