An Evolutionary Trust Game for the Sharing Economy

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***Abstract*—In this paper, we present an evolutionary trust game to investigate the formation of trust in the so-called sharing economy from a population perspective. To the best of our knowledge, this is the first attempt to model trust in the sharing economy using the evolutionary game theory framework. Our sharing economy trust model consists of four types of players: a trustworthy provider, an untrustworthy provider, a trustworthy consumer, and an untrustworthy consumer. Through systematic simulation experiments, five different scenarios with varying proportions and types of providers and consumers were considered. Our results show that each type of players influences the existence and survival of other types of players, and untrustworthy players do not necessarily dominate the population even when the temptation to defect (i.e., to be untrustworthy) is high. Our findings may have important implications for understanding the emergence of trust in the context of sharing economy transactions.**

I. Introduction

Many forms of social and economic transactions build on the decision maker's expectation that one's transaction partner will not behave opportunistically and deviate from previously made agreements. This expectation is commonly conceptualized as *trust*, that is, the "belief that the other party will behave in a dependable, ethical, and socially appropriate manner" ([1], p. 53). The belief that another party will behave in a trustworthy way is particularly important for Internet-facilitated transactions, which are typically characterized by a higher level of uncertainty about the other party's behavioral intentions, compared to offline channels [2]. In the context of business-to-consumer (B2C) online shopping, a consumer will only make a purchase from an e-vendor if they trust that it will deliver the product once a payment was received.

In recent years, there has been a rapid proliferation of new platforms that facilitate consumer-to-consumer (C2C) transactions between private individuals. In this so-called *sharing economy*, consumers share access to private resources such as accommodation (Airbnb), tools (Zilok), or rides and vehicles (BlaBlaCar) with other users. In contrast to other forms of C2C commerce such as selling commodities on eBay, transactions in this sharing economy do not involve transfer of ownership. Instead, it offers new opportunities for private individuals (1) to act as providers and to monetize their private assets in multiple transactions without loss of ownership, and (2) to act as consumers and get access to a broader range of resources, potentially at lower prices than by conventional modes of consumption. Beyond such economic motives, the literature has further identified several aspects that drive individual engagement in sharing economy transactions, including social and sustainability reasons [3], [4]. However, any of these motives will only translate into actions if there is a substantial level of trust between the transaction partners.

In contrast to 'traditional' e-commerce, sharing economy transactions are commonly carried out in the private sphere of the provider, hence entailing some level of personal interaction and a high level of exposure as they risk damage or theft to their private assets (e.g., ride and accommodation sharing). To this end, a transaction does not only require the consumer's belief that the *provider* will behave trustworthily, but also the provider's belief that the *consumer* will behave trustworthily. At the nexus of this mutual trusting constellation, emerging research aims to provide insights into how trust can be established in the sharing economy, typically building on surveys [4], [5] and human lab experiments [6], [7]. What is common to these studies though, is that they focus on the perspectives of individual users and do not capture the potential insights that could be gained through studying the evolution of trust and trustworthiness in a sharing economy context at the population level over the course of multiple periods.

In this paper, we use evolutionary game theory (EGT) as a framework and propose a sharing economy trust model to bridge the above-mentioned gap. Within the EGT framework, social dilemma models such as the Prisoner's Dilemma and Snowdrift games have been adopted to study cooperative phenomena extensively. In contrast, only limited studies have used EGT to model trust (e.g., see [8]–[10]). In our trust model, players can be either *providers* or *consumers*. Providers and consumers may choose to be trustworthy or untrustworthy, thereby giving rise to four possible strategies: being a *trustworthy provider* (TP), being an *untrustworthy provider* (UP), being a *trustworthy consumer* (TC), and being an *untrustworthy consumer* (UC). Given the complexity of analyzing the evolutionary dynamics of a population with four possible types of players, we opt for agent-based modeling [11] over a purely analytical approach. Agent-based modeling is a computational approach where individuals in the population are represented by agents. Each agent is given an opportunity to act autonomously based on a set of rigorous rules.

In Section II, we discuss some related work and the

978-1-5090-4601-0/17/$31.00

importance of trust in the sharing economy. The proposed game model is then described in Section III. After that, the experimental setup and results are presented in Section IV. Finally, we draw conclusions and outline directions for future work in Section V.

II. Background and Motivation

A. From Classical to Evolutionary Game Theory

Game theory offers an abstract framework of real-life situations where different interaction scenarios between individuals can be investigated. Typically, the individuals playing a game against each other are assumed to be *fully rational* and have a set of *strategies* to choose from. Here, a strategy provides a complete definition of how an individual will play the game. That is, it determines the action each individual will make. The *payoff* then depends on the chosen strategy and the strategy of their opponent.

However, there have been arguments that the assumption of full rationality of players in classical game theory is unrealistic in practice [12]–[14]. Moreover, there appears to be a lack of dynamical view towards players with the controversial assumption of instantaneous interactions [14]. In view of these issues, the standard game theory approach has been extended by adding *evolution* as a new dimension (hence 'evolutionary' game theory or EGT in short), thereby dropping the unrealistic assumption of full rationality. To this end, the concepts of *population of players* and interpretation of payoff as *fitness* have been considered, which naturally lead to a dynamical approach [15], [16]. Originating from the work of Maynard Smith and Price [17] in 1973, the fundamental idea of EGT is that evolution takes part in spreading the successful strategies (traits) in the population. Such a process is done via *frequency-dependent selection*, which means that the spread of a particular strategy depends on the relative abundances of the types of strategies in the population. On one hand, strategies that have higher fitness reproduce quickly. On the other hand, strategies that perform poorly have less chance to propagate.

In the past four decades, EGT has been used extensively as a standard framework for understanding the emergence and maintenance of cooperation. Based on the development and study of different social dilemma models, significant advancements have been made not only in evolutionary biology but also in other fields such as anthropology, computer science, economics, operations research, physics, political and social sciences, and psychology, among others (see Chapter 1 of [18] for historical EGT developments). Two of the most commonly studied models of cooperation are the Prisoner's Dilemma [19] and Snowdrift [20] games.

B. Evolutionary Trust Games

Different from models of cooperation, trust games are sequential in nature. In a classical trust game, there are two types of players: an investor and a trustee [21]. The investor *first* decides whether to trust the trustee, and *then* the trustee decides whether to act trustworthily or not. Trust games have gained attention from the EGT community fairly recently, where researchers found that an evolutionary trust game that adds information and permits a partner choice for investors can alter the nature of game interaction and lead to the evolution of fully trusting and marginally trustworthy behavior [9]. Subsequently, Tarnita [10] explored non-random interactions in a structured environment using the classical evolutionary trust game. She showed that, in the limit of weak selection, the population structure biases selection towards strategies that are both trusting and trustworthy. Abbass et al. [8] introduced an N-player trust game, and showed that in a well-mixed environment even with just one single untrustworthy player in the initial population, untrustworthiness would spread very quickly leading to the extinction of investors. However, they also noticed that a fraction of the population would always remain trustworthy, even in the absence of investors.

Clearly, only a limited number of studies related to evolutionary trust games can be found in the relevant literature. Our current work represents the very first attempt to study evolutionary dynamics of four possible strategies – TP, UP, TC, and UC – in the sharing economy context.

C. Importance of Trust in the Sharing Economy

Over the past two decades, trust has been recognized as a critical factor for virtually all forms of exchange in B2C and C2C e-commerce [1], [22]. It is worth pointing out that the idiosyncrasies of sharing transactions add several levels of complexity that commonly do not exist in conventional e-commerce transactions [3], [7]. In particular, sharing transactions typically include personal interaction between the involved parties in the real world, especially in the context of co-usage sharing where the consumer and the provider share accommodation or a ride over a period of several hours or days [23], [24]. Furthermore, as there is no transfer of ownership, the provider faces a high level of exposure due to potential damage or theft of high value assets. The implications of these characteristics on trusting relationships are manifold [25], rendering trust as the very *currency* of the sharing economy [26], [27] and requiring a high level of mutual trust between the consumer and the provider. Studying trust in this context is therefore highly necessary.

First, while a *consumer's trust* in the provider is a prerequisite for any e-commerce transaction, the nature of sharing transactions generally requires a higher level of trust in the provider than conventional transactions. In particular, while a *trustworthy provider* would provide access to resources as agreed upon, an *untrustworthy provider* may deviate from previous agreements by providing accommodation of much lower quality than what was promised or not even showing up at all, leaving the consumer stranded – a similar notion applies to ride sharing [7]. While such contract violations represent obvious and substantial process risks to the consumer, there is another, more subtle dimension. Since a person's trustworthiness is inherently linked to the social appropriateness of their behavior [1], the consumer's trust in the provider is a critical component for the expected level of social satisfaction associated with the transaction [28].

Second, while a *provider's trust* in the consumer is of comparably little importance in selling activities (e.g., eBay, Taobao), the provider's high level of economic and social exposure requires substantially higher levels of trust. While a *trustworthy consumer* would behave in a culturally, socially, legally, and ethically acceptable manner during a sharing transaction, an *untrustworthy consumer* may cause substantial financial and/or psychological distress to the provider (e.g., due to theft or damage of the provider's private assets).

III. The Sharing Economy Trust Model

A. Game Definitions and Payoffs

Our sharing economy trust model consists of a finite set of agents occupying the nodes of an 'online' network, and the edges denote interactions or 'transactions' between them (both for accumulating payoffs and strategy updating [29]). Each agent i can choose one of the four possible strategies:

- TP: A trustworthy provider who offers an asset as promised;
- UP: An untrustworthy provider who offers an asset with markedly lower levels of product/service quality compared to what was promised beforehand;
- TC: A trustworthy consumer who uses an asset facilitated by a provider in a dependable, socially and economically appropriate manner;
- UC: An untrustworthy consumer who uses an asset facilitated by a provider in an excessive, socially or economically inappropriate manner (e.g., by damaging or stealing it, molesting others, etc.).

The game is based on pairwise interactions [30]. That is, every agent interacts or 'transacts' with other directly connected agents in pairs. All agents in the population play the game over a fixed number of time steps. The initial population of *pop* agents is generated at random with the four types of players: k_{TP} is the number of trustworthy providers, k_{UP} the number of untrustworthy providers, k_{TC} the number of trustworthy consumers, and k_{UC} the number of untrustworthy consumers, with $k_{TP} + k_{UP} + k_{TC} + k_{UC} = pop$. The net wealth of individual agents, calculated based on their payoffs, is determined according to the strategy adopted by themselves and those they interact with. For example, the total net wealth w_i of focal agent i is calculated by adding the payoff values of all its interactions with other agents. See Table I for the payoff matrix.

TABLE I. Payoffs for the sharing economy trust game.

Providers	Consumers TC	Consumers UC
TP	R, R	$-S, Temp$
UP	$X, -X$	$X, -X$

Here, $Temp$ is the temptation for a consumer to be untrustworthy towards a trustworthy provider; R is the reward when both the provider and consumer are trustworthy; S is the sucker punishment for a trustworthy provider when a consumer is untrustworthy; and X is the value an untrustworthy provider keeps and a consumer (trustworthy or untrustworthy) pays after a transaction is initiated. Note that when both players interacting with each other are of the same role (i.e., both are consumers or both are providers), no payoff is given.

The payoff matrix in Table I, which measures the cost and gain for the different types of players during the game, is designed based on the fact that the provider-consumer interaction in typical sharing scenarios constitutes a social dilemma situation, where both players have an incentive to deviate from the initial agreement, hence requiring substantial levels of mutual trust [7]. In this context, taking on a trustworthy role represents the cooperative strategy, whereas taking on the untrustworthy role represents the strategy of defection. There exists a Pareto-optimal but unstable constellation of mutual cooperation in which both the provider and the consumer receive payoffs of R. In this situation, both parties execute the sharing transaction as per the previously agreed upon conditions. However, if a consumer decides to defect against a trustworthy provider, a $Temp$ payoff is given to the untrustworthy consumer at the cost $-S$ of the trustworthy provider. If providers act in an untrustworthy way, a payoff of X is given to them while the consumers are penalized with a payoff of $-X$. This means untrustworthy players are able to exploit their counterparts' good faith economically, hence giving untrustworthy strategies the edge over trustworthy strategies.

As sharing economy platforms normally would provide their users with insurance (e.g., for damages or when consumers are left stranded), which mitigates a substantial amount of the costs for interacting with untrustworthy counterparts, in this study we model X and S to be smaller than R. That is:

$$2 \cdot R > Temp > R > S > X. \tag{1}$$

We are also interested in the global net wealth of the population W, calculated as $W = \sum_{i=1}^{pop} w_i$. By running the model for a maximum number of time steps in a synchronous manner, at each time step t agents in the population decide on which strategies to choose based on the population state of the previous time step (i.e., $t-1$). This means that the actions of others at time step t will not affect the focal agent's decision during the same time step [11].

B. Linking Players' Actions via a Social Network

Transactions in the sharing economy are facilitated by matching individuals who have mutual interest in sharing resources, typically through an online network. We use a social network, defined by a set of actors/agents and the relationships (ties) among them, to represent this online network. The intuition for this modeling is that each agent has a relationship with (1) providers who can provide the resources they need and (2) consumers who demand assets that the agents can provide to them. In other words, the network reflects a matching of complementary provider-consumer relationships of private individuals rather than a social relationship in the traditional sense. In this paper, all agents in the population are placed on a real social network. This real network corresponds to the email network of a university in Tarragona, Spain [31].

C. Strategy Update

The strategies of agents (i.e., TP, UP, TC, and UC) can change during the game, as each agent is given an opportunity to update its strategy through an evolutionary update process. We may perceive this activity of strategy update as information exchange in a social learning process, where agents in the population imitate the strategies of others [29]. Strategy imitation occurs in all time steps during the game. At time step t, a focal agent (independent from its strategy) evaluates its previous payoff in $t-1$ and decides whether to imitate a connected agent's strategy or not by applying an evolutionary update rule. Evolutionary update rules of imitative nature represent a situation where bounded rationality or lack of information forces players to copy (imitate) others' strategies [32]. These update rules are widely employed in the relevant literature to model evolutionary dynamics.

For this paper, we use the proportional imitation rule [33], which is a pairwise and stochastic update rule. An agent i may adopt one of the four possible strategies for the game (i.e., TP, UP, TC, and UC) from another agent j interacting with i at time step t. Specifically, the update rule works as follows. Let us denote a randomly selected neighbor of focal agent i as j. The rule first evaluates if the individual payoff value of j in the previous time step, w_j^{t-1}, is higher than that of the focal agent (w_i^{t-1}). If it is higher, agent i will adopt the strategy of agent j by a probability that depends on the difference between their payoffs:

$$prob_i^t j = \frac{\max\{0, w_j^{t-1} - w_i^{t-1}\}}{\phi}, \tag{2}$$

where ϕ is the difference of maximum and minimum possible individual net wealth between two arbitrary agents at time step $t-1$ to have $prob_i^t j \in [0,1]$.

IV. Experiments and Results

A. Experimental Setup

Our simulation experiments were run with a population of 1,133 agents (i.e., $pop = 1,133$, the number of nodes the real social network used has [31]). The network's clustering coefficient is 0.254 and its average shortest path length is 3.606. We set the simulations to $5,000$ time steps and all of them were repeated for 50 independent Monte Carlo runs. Reported results were calculated by averaging the last 1,250 time steps (i.e., the last 25%) of each run. In every time step, each agent plays the game iteratively with other directly connected agents and decides whether to change its strategy. Payoffs of the agents were calculated based on the payoff matrix of Table I. Here, we set $Temp = 40$, $S = 20$, $X = 10$.

We report on the results for different values of the reward parameter R from 21 to 39, which cover three different trust situations ranging from the game being *easier*, *moderate* and *harder*. This range of values has been chosen so that the constraint of Eq. 1 is not violated. We also report on results of five different scenarios for the initial population conditions by setting the values of k_{TP}, k_{TC}, k_{TC} and k_{UC}, which determine the numbers of initial players that have strategies TP, UP, TC, UC, respectively, to:

- Scenario 1: different types of players are divided proportionally ($k_{TP} \approx k_{UP} \approx k_{TC} \approx k_{UC}$).
- Scenario 2: more consumers than providers ($k_{TP} \approx k_{UP} \approx 0.05 \cdot pop$ and $k_{TC} \approx k_{UC} \approx 0.45 \cdot pop$).
- Scenario 3: more providers than consumers ($k_{TP} \approx k_{UP} \approx 0.45 \cdot pop$ and $k_{TC} \approx k_{UC} \approx 0.05 \cdot pop$).
- Scenario 4: more untrustworthy players than trustworthy players ($k_{TP} \approx k_{TC} \approx 0.05 \cdot pop$ and $k_{UP} \approx k_{UC} \approx 0.45 \cdot pop$).
- Scenario 5: more trustworthy players than untrustworthy players ($k_{TP} \approx k_{TC} \approx 0.45 \cdot pop$ and $k_{UP} \approx k_{UC} \approx 0.05 \cdot pop$).

B. Analysis of the Results

Figure 1 shows the influence of the range of reward values considered, i.e., $R \in [21, 39]$, in the final population state for each of the five different scenarios of the game. For higher reward values. e.g., R equals to or higher than 33, the game is rather 'easy' and predictable. Around such R values, we see that the population is dominated by TP and TC players except when the initial population started with a small number of TP and TC (i.e., 5% each). This trend is fully expected. When the game is 'moderate', e.g., R between 27 and 33, we can see that the total number of trustworthy players decreases while the total number of untrustworthy players increases in general. This is again expected given the game's payoffs (see Table I). The transition point of around $R = 30$ ($\approx 40 - 10$) for untrustworthy players to rise and trustworthy players to drop makes sense, since this is the mark that is close to the difference between the temptation value for a player to act as an untrustworthy consumer ($Temp = 40$) and the value an untrustworthy provider keeps and a consumer pays after a transaction is initiated ($X = 10$). It is worth noting that the situation is quite different (as expected) when an initial population has a small number of trustworthy players. In a situation like this, UP players are dominant regardless of the value of R, as shown in Scenario 4 of Figure 1.

Moving our attention to the more 'difficult' part of the game, e.g., when R is between 21 and 25, the expectation was that untrustworthy players will continue to prevail. An interesting observation, however, is that this is not always the case. Two points worth noting here are (1) the number of UC players – the orange dashed line in the plots of Figure 1 – actually decreases from $R = 25$ onwards in Scenarios 1, 2, 3, and 5; and (2) TP and TC players are 'revived' while the number of UP (the blue dashed line in Figure 1) decreases in Scenarios 3 and 5. These are rather unexpected.

Taking a closer look at the plots, we notice that when the number of UC increases, there is always a corresponding decrease in the number of TP. This is particularly clear in Scenarios 1, 3, and 5. When the number of UP increases, both TC and UC decrease. As the number of UC reduces, the number of TP goes back up (see Scenarios 1, 3, and 5), thereby explaining the 'revival' of trustworthy players. In Scenario 1, with an equal footage for different types of players in the initial population, the number of UP continues to surge when the game is very much in favor of them (i.e., $R = 21$), leading to the decrease of TC and, in turn, the decrease of TP. In Scenario 3, however, the limited number of TC and UC in the initial population means UP will decrease. Meanwhile, the abundance of TP helps the spread of TC. Likewise, the limited number of UP and UC in the initial population in Scenario 5 means TP and TC can easily 'cooperate' to promote trust and trustworthiness.

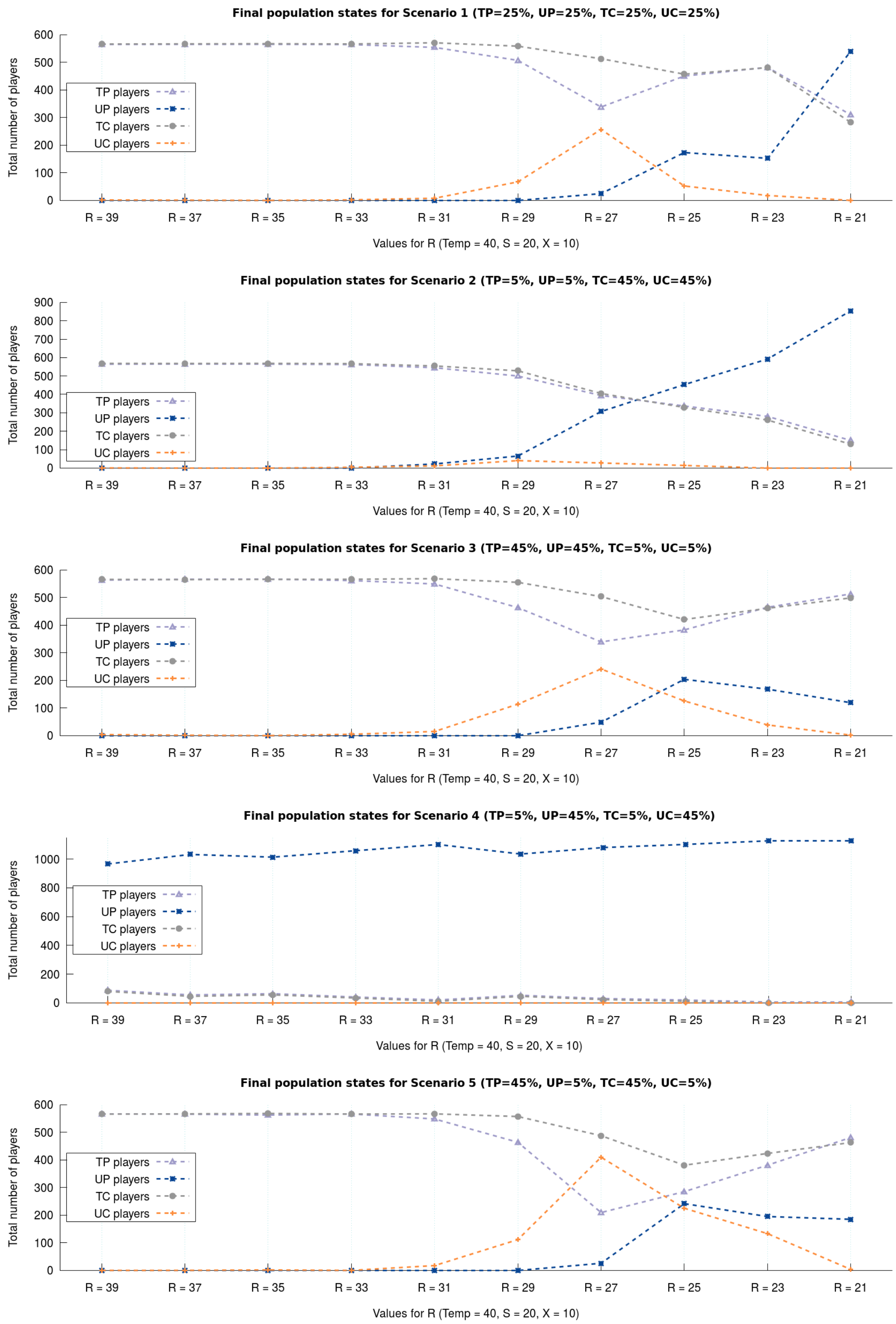

Fig. 1. (Color online) Final population states (numbers of TP, UP, TC and UC players) for the five defined scenarios when having different R values.

It is obvious from our analysis to this point that each type of players will impact on the existence and survival of other types of players, and that the initial population distributions matter. Delving further into Scenarios 1, 3 and 5, we show the time series plots of these scenarios in Figures 2, 3 and 4 with $R =$ 21, 25 and 27. From the figures, we can see reciprocal types of interactions between trustworthy players and untrustworthy providers. Especially when the game is challenging, TP and TC players clearly 'work' hand-in-hand to help each other out, even in a situation when the population started with only 5% of TC (see Figure 3). It is interesting to see in Figure 5 that higher global net wealth values are achieved in Scenarios 3 and 5 when $R = 21$ and 23 compared to $R = 25$ and 27. This undoubtedly reflects the importance of trustworthy players in the population.

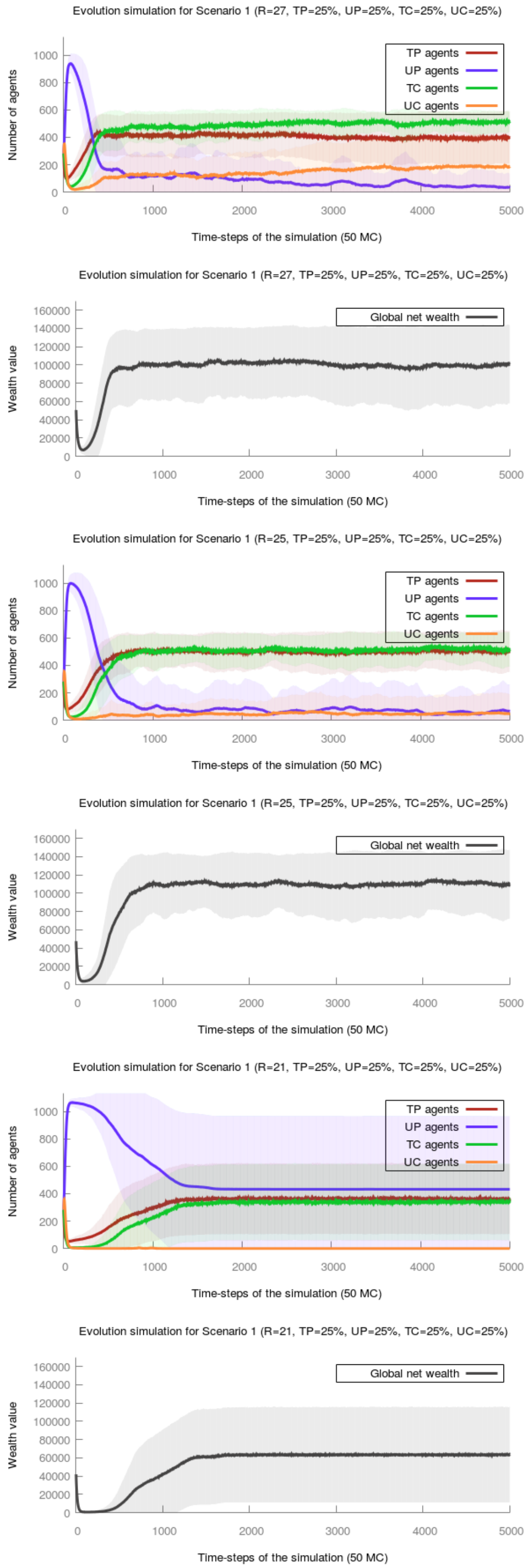

Fig. 2. (Color online) Time-series evolution of the number of players and net wealth values in the 5,000 steps of the simulation for the first scenario when R equals to $27, 25$, and 21.

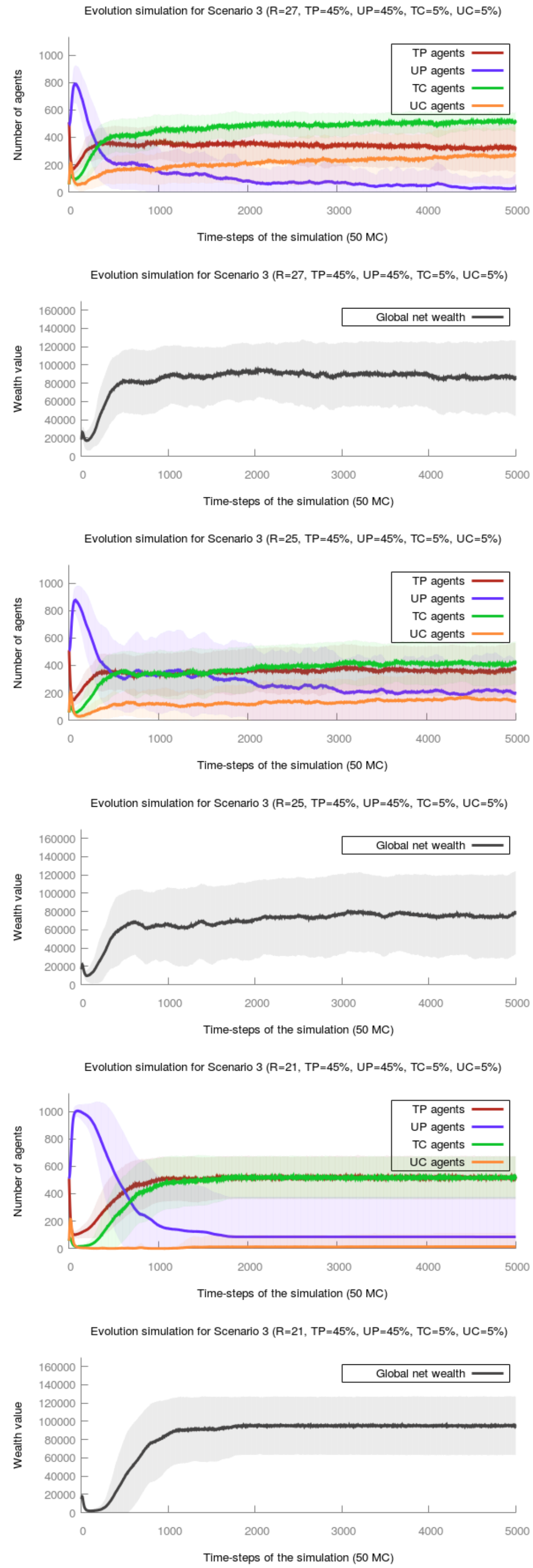

Fig. 3. (Color online) Time-series evolution of the number of players and net wealth values in the 5,000 steps of the simulation for the third scenario when R equals to $27, 25$, and 21.

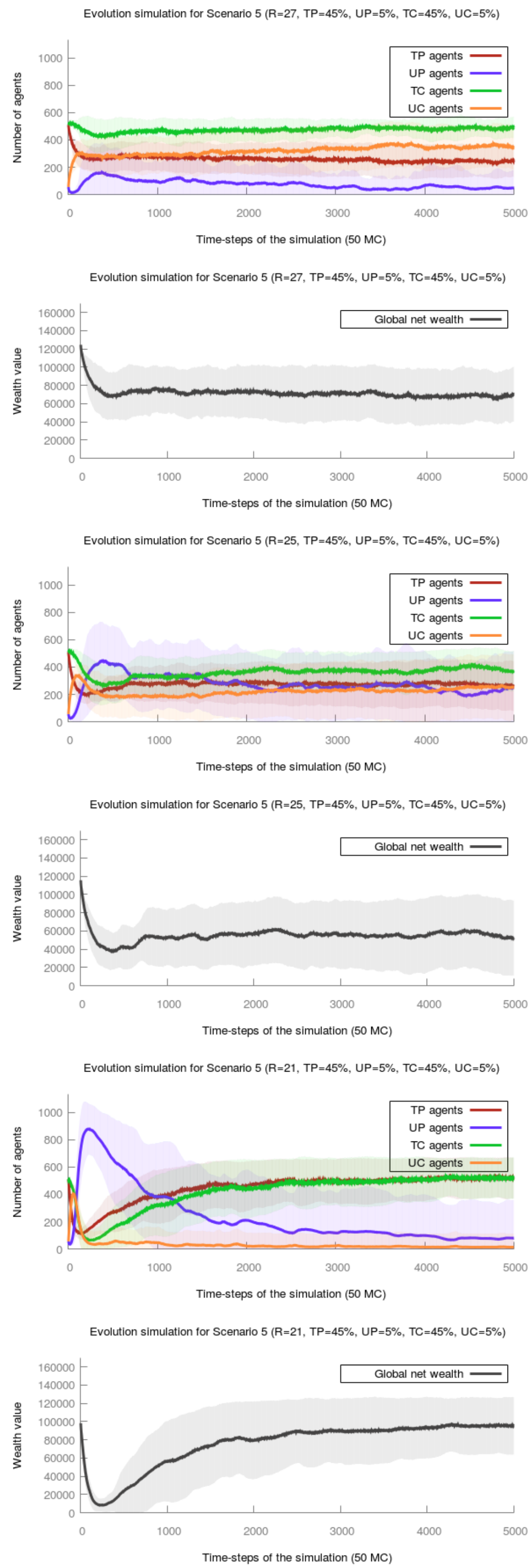

Fig. 4. (Color online) Time-series evolution of the number of players and net wealth values in the 5,000 steps of the simulation for the fifth scenario when R equals to $27, 25$, and 21.

V. Concluding Remarks and Future Work

In this paper, we presented a novel evolutionary trust game to investigate the formation of trust in the sharing economy from a population perspective. The importance of trust in this context is clear, as trusting relationships involved here are complex. Our sharing economy trust model consists of a finite set of agents occupying the nodes of a real network, and the edges denote interactions between them. Every agent can choose between being a trustworthy provider, an untrustworthy provider, a trustworthy consumer, and an untrustworthy consumer. Systematic computational experiments across a range of reward values (i.e., R) and different initial population distributions showed that trust can be formed when the reward values are high, except if the initial population has limited trustworthy players (e.g., only 10% of them). Even when the reward values are low, as long as the initial population started with not too many untrustworthy consumers, trustworthy players – both providers and consumers – can still prevail.

The simulation results also uncovered a surprising phenomenon, i.e., untrustworthy consumers are never dominant. Detailed analysis revealed that even though untrustworthy consumers can exploit trustworthy providers, they are 'punished' by untrustworthy providers. On the contrary, trustworthy providers and consumers cooperate with each other. This points to the importance of a balancing effect of trustworthiness due to the mutual trust constellation. More specifically, untrustworthiness of the consumers (e.g., causing financial and/or psychological costs to the provider due to theft or damage) is reciprocated with untrustworthy behavior by the providers (e.g., deviating from the agreed upon level of access to the asset), driving consumers to behave trustworthy. Taken as a whole, this balancing effect, stemming from the high level of mutual trust required between the consumer and the provider, drives higher welfare levels in the sharing economy.

While the focus of this study was on the reward values received by trustworthy providers and consumers, our future work will investigate further the parameter (i.e., X) controlling the values to be kept by untrustworthy providers and paid by both trustworthy and untrustworthy consumers. Different network topologies (e.g., see [34], [35]), which impact information diffusion differently, should also be considered taking into account different sharing economy scenarios.

Acknowledgments

The authors would like to thank the 5 anonymous reviewers for feedback, and acknowledge the support for this work from the Australian Government's 2016 Endeavour Research Fellowship, Spanish Ministerio de Economía y Competitividad under the NEWSOCO project (ref. TIN2015-67661-P), and the Andalusian Department of Innovación, Ciencia y Empresa under Project TIC2011-7745, both including European Regional Development Funds (ERDF).

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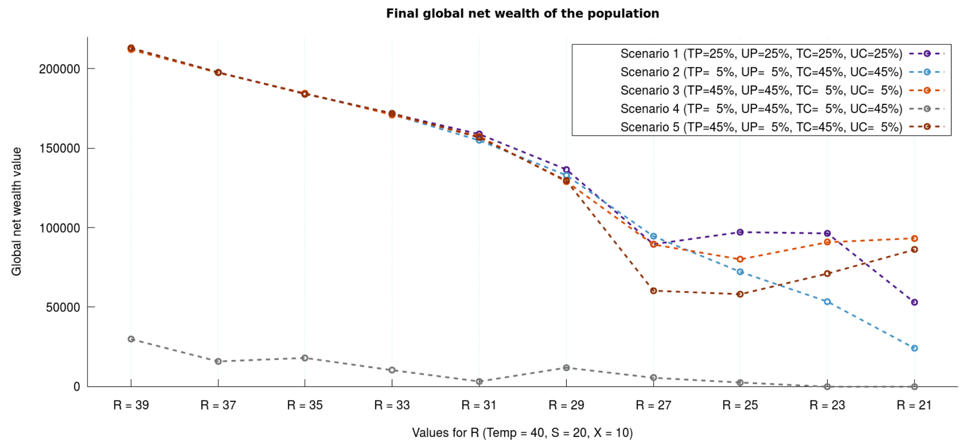

Fig. 5. (Color online) Final global net wealth of the population for the five defined scenarios when having different R values.

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