Banned from the Sharing Economy
An Agent-based Model of the Peer-to-Peer Distribution of Consumer Goods

Adrien Querbes
Department of Social and Decision Sciences, Carnegie Mellon University
5000 Forbes Ave, Pittsburgh, PA 15213, USA
e-mail: querbes@andrew.cmu.edu

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Abstract. The emergence of profit-based online platforms for the peer-to-peer sharing of consumer goods provides new means for the end users to derive profit from their possessions. The success of these platforms relies heavily on the behavior of their participants. Using an agent-based model simulating these behaviors via different scenarios, we show how these mechanisms are efficient to improve the information held by the participants. Analyzing the outcomes of these scenarios as the payoffs of a coordination game, we find contrasting results regarding the benefits obtained by each side of the platform: exclusion of some categories of customers, overpricing of some categories of goods, or under-activity on both sides.

Keywords: customer reviews, agent-based model, sharing economy, decentralized coordination

1 Introduction

The Internet has dramatically changed the production and distribution of consumer goods. Thanks to the commoditization of online access, users have seized the opportunity to bypass – and often surpass – well-established businesses for production and trade. In this research, we focus on the online platforms that give anyone an opportunity to share consumer goods, in order to use more efficiently and to generate an income from possessions. These platforms – such as airbnb.com, UBER.com or feastly.com – operate in a grey area between traditional marketplaces (supplied by professionals) and the not-for-profit part of the ‘sharing economy’. Their proximity with traditional marketplaces makes them attractive to new participants, while they generate many concerns from the incumbent firms (e.g. Airbnb versus the hospitality industry, Uber versus the taxi companies). As economists, we see here unprecedented mar-
ket platforms, based on profitable sharing, professional-level services, social networks and online reviews, covering many industries, such as transportation, accommodation or catering.

These peer-to-peer platforms have some market characteristics that are barely studied jointly. The first one is the information scarcity affecting both sides of the market platform. Usually, such uncertainty is reduced via the standardization of products (norms, expectations of distribution channels or externalization of components) and the standardization of tastes (marketing and conformity). In a peer-to-peer market, the variety of products and tastes might be overwhelming, making it very difficult for the participants to assess the quality or evaluate the price of products. The second characteristic is the reliance on the decentralized governance of transactions. The transactions are governed by platform rules and complex peer-to-peer mechanisms supposed to facilitate and control the transactions. The core element of this system is the review written by the customer. The aggregation of these reviews provides the basis for a self-organized learning (creation and sharing of market information), while introducing inertia and the overabundance of – potentially irrelevant – information. The third characteristic is the permeability: participants can switch sides and entry is easy. Similarly, these platforms rely heavily on the sense of community, while stimulating self-entrepreneurship and the ability to grasp opportunities. This apparent contradiction creates a very interesting tension between individual and collective behaviors.

Aggregating these characteristics leads us to our question: are we witnessing the emergence of a new front for the economy or just the experimentations of niche users? To answer it, we will look at the intrinsic properties of these markets, via the simulation of different scenarios of evolution. The simulations are of major interest here, because of the scarcity and sensitivity of the data related to these new marketplaces. Such databases are difficult to gather, due to the novelty and variability of the business models, together with the evolution of participants. Besides the reluctance of platforms’ owners to share it, data would be yet insufficient to draw robust conclusions. Moreover, simulations give the opportunity to test existing theories, by putting together theories and empirical findings from various scientific horizons.

As a result, our simulations show how the agents’ behaviors influence strongly the attraction and revenue generated by these platforms. In summary, in Section 4, we study four scenarios based on different behavioral characteristics of the agents, by monitoring the prices, user satisfaction and transactions emerging on this simulated platform. The first scenario shows how the suppliers can make the right price adjustments without any direct or centralized knowledge of the market as a whole (i.e. demand curve and product quality relative to the market). The other scenarios show how the individual decisions of suppliers may generate a collective benefit for them while excluding large groups of customers, and, in one case, how their behavior can be detrimental to both sides. Based on a constant population, the results give a strong foundation to our follow-up research: the introduction of dynamics (i.e. entry and exit). In Section 5, we discuss these scenarios using a game theory framework to provide insights for the governance and regulation of these new platforms. Before that, in Section 2, we review the literature to establish the main hypotheses governing the agent-based model, and, in Section 3, we introduce the static version of the model.
2 Literature Review and Hypotheses

Our research follows the tradition of micro-founded market simulations that can be found in Gode and Sunder [1993], and Kirman and Vriend [2001]. Such an approach bifurcates from the classic hypotheses of profit maximization, walrasian auctioneer and perfect information, due to their lack of plausibility [Axtell, 2005]. This makes it particularly interesting to analyze the macro-outcomes of these simulations not in terms of equilibria, but via performance indices, such as the distribution of prices or the extraction of surplus.

In order to adapt this tradition to the characteristics of peer-to-peer platforms, some recombination is necessary. From Gode and Sunder [1993], we borrow three assumptions: (i) demand and supply functions can be derived from simple budget constraints rather than maximization-behavior based on costs; (ii) the budget constraints being private, the demand and supply functions are unknown to the participants; (iii) the transactions occur on single units only. By giving the opportunity to anyone of supplying consumer goods, peer-to-peer platforms encourage individuals to extract revenue from their existing possessions. Even if the platform policies may advise to mimic professional standards and norms, supplier costs are mostly opportunity costs related to the willingness to make transactions with strangers. In a nutshell: the quantity is capped (number of guests in an accommodation, number of seats in a car traveling on a specific route, number of meals that can be cooked and so on); the quality is mostly fixed by the initial investment; and the price is related to personal preferences or constraints more than production costs.

However, unlike the discussed models, customers cannot bargain the prices\(^1\). Price adjustments are made sequentially, via experimentations made outside the transactions. Kirman and Vriend [2001] – when they analyzed the dynamics and emergent properties of Marseille’s fish market – use the concept of *loyalty* as coordination and learning device for repeated transactions. Such a device is particularly relevant to model peer-to-peer platforms, where social and non-anonymous relationships shape the transactions. However, on these platforms, most of the transactions are involving new participants, so the tacit and idiosyncratic loyalty has to be replaced by a transmissible information, namely the customer review. In fact, the platforms depend heavily on this, because this helps to build trust and reputation. Customers are expected to give credit and contribute to reviews, mostly to determine the quality of goods that would be considered as ‘experience goods’ and, therefore, to oppose moral hazard. Facing imperfect information about quality, the literature predicts various nuisances for customers: market concentration, limited incentives to supply the highest quality, overpricing (see for instance Shapiro [1982] and Allen [1984]).

On one hand, one can question the happenstance of opportunistic behavior on platforms that promote altruism. As an advocate of non-market peer production, Benkler [2006] shows how introducing monetary rewards in transactions that could be provid-

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\(^1\) One of the innovations leading to the emergence of these platforms was to provide a secured payment system directly on the platform. The centralized payment system can also be related to the business model of these platforms, i.e. debiting fees on the transactions.
ed voluntarily via social relations, affect the content of these transactions. The transition from a non-profit to a profit-oriented sharing economy is not harmless: “money-oriented motivations are different from socially oriented motivations” [Benkler, 2006: 97]. For instance, Zervas et al. [2014] point up how Airbnb has affected a specific segment of the hospitality industry, the lower-end hotels. Hotels offering business services do not suffer from the emergence of this platform. Hence, we assume that customers on these platforms are interested in getting lower prices when traditional offers exist. Equally, Teubner et al. [2013] conducted an experiment demonstrating how the reduction of anonymity (i.e. exchanging with individuals rather than groups) increases the contributions. This is important to develop trust in these emerging markets. Based on this finding, we wonder whether the profit-oriented peer-to-peer production would exhibit more price inelasticity of the demand, where excessive prices would be more accepted when they are charged by peers rather than by anonymous firms. Besides, suppliers find here a previously-unexploited source of revenue, so the fear to lose it – due to a wrong strategy – is low.

On the other hand, one can also question the role of customer reviews as a protection against opportunism. Zhu and Zhang [2010] show how the influence of reviews is depending on products and consumers. For new (not well known) products and advanced Internet users – characteristics that match with our research – reviews are influential. Duan et al. [2008] put forward “the dual nature of online user reviews”: (i) “consumer’s assessment of product quality”, (ii) “product awareness among consumers”. They find that higher ratings do not affect the sales, while the number of reviews is correlated with the sales (cf. bandwagon effect). Similarly, Park et al. [2007] emphasizes that quantity together with the quality stated by the reviews have an influence on purchases. In his literature review, Dellarocas [2003] finds a rather general consensus that positive reviews lead to higher prices. At the same time, he shows how reviews have to be handled cautiously, because: (i) a critical mass of reviews is necessary to derive a strategy, (ii) platform owners control how the reviews are provided; and (iii) reviews lack context. This idea is shared by Bolton et al. [2004] who observe the underrepresentation of negative reviews, because reviewers fear retaliations.

We learn from this literature on customer reviews that reviews contribute to reputation building (with a risk of bandwagon effect), while being used as a proxy rather than a fair source of information. For instance, Fradkin [2014] has analyzed search data from Airbnb and he shows that potential customers filter the listings based on objective variables (mostly the location and maximum price) before browsing the remaining listings and evaluating more subjective characteristics (including the number and text of reviews). Such a distinction can be found in the model of an online market with a self-selection bias of consumer reviews built by Li and Hitt [2008]. In their model, they distinguish two classes of attributes: the ‘search attributes’ which can be inspected before the transaction and the ‘experience attributes’ which are specific to each consumer based on its experience of the product. A more general approach is proposed by Valente [2012] with an algorithm of product selection including empirically-validated hypothesis on the behavior of bounded rational and adaptive customers. We will follow this algorithm in the model. In its simplest version, products are defined by two characteristics (quality and price). Customers have an order of
preference for these characteristics. Based on this order, they cyclically reduce the set of products to the products that provide the best results on this characteristic, until there is only one product left.

3 Model

The objective of these simulations is to understand the evolution of a peer-to-peer market guided by decentralized decisions and customer reviews. We model the emergence of this market as an online platform connecting agents who either supply or request similar consumer goods and keep tracks of the previous transactions. Suppliers expect to extract revenue from the transactions, while customers expect to pay a price which is consistent with the product quality. Customers express their (dis)satisfaction by writing reviews regarding their transactions.

At this stage, simulations are performed with a constant population of agents. Our research plan is to build here a robust model and to develop a clear understanding of its behavior, in order to develop later a dynamic version of the model, introducing the dynamic attractivity to new users and the exit of unsatisfied agents. In order to make the presentation of the model more readable, we will present this model as an online platform for accommodations (such as Airbnb): each agent in the simulated population is either a Host or a Guest. The constant population of agents is \( P = H + G \) with \( H \) the number of Hosts, \( G \) the number of Guests. Each agent is initialized with a fixed personal characteristic: for a Guest, this is her reservation price \( r \), i.e. the maximum price she is willing to pay for the accommodation; for a Host, this is the quality level of his accommodation \( q \). Both \( r \) and \( q \) are drawn randomly from the uniform distribution \( U(0,1) \).

For the Guests, in our simple design, the fair price of an accommodation is \( p = q \). When the simulation starts (at simulation step \( t = 1 \)), the Hosts do not know how to evaluate their accommodations. Hence, they set randomly a starting price \( p_1 \sim U(0,1) \). By setting \( r, q \), and \( p_1 \) following the same distribution, we assume that there is a possible market equilibrium where each Guest finds a Host with \( p = q = r \). We also assume that at each step \( t \), only a subset of Guests \( G^* = H \) chosen randomly among \( G \) are looking for an accommodation, i.e. there is neither systemic shortage nor surplus. In turn, each one will try to find an accommodation. If she succeeds, she will write a review regarding her experience of the accommodation quality. Once the turns are over, the Hosts have the opportunity to adjust their price.

When looking for an accommodation, a Guest applies the following procedure:

- First, she reduces the set of Hosts to a subset \( H_r \), limited to Hosts with \( p \leq r \).
  - If \( H_r = 0 \), i.e. no Hosts match with this condition, she is considered unmatched and her search ends.
  - If \( H_r > c \), she selects randomly \( c \) Hosts from \( H_r \). \( c \in \mathbb{N} \) refers to the cognitive ability, i.e. the amount of information that a person can handle.
Then, she selects one accommodation depending on her preferences.

- If she is *quality-oriented*, she computes a weight \( W_h \) for each Host \( h \in H_r \).
  This weight adds up the past reviews received by the Host, \( W_h = \sum_{t=1}^{t^*} M_{h,t} + 1 \), with \( t^* \) being the current step. The platform stores the reviews via a simple grade \( M_{h,t} \in [0,1] \) (see below). Then, she chooses one Host randomly with a probability proportional to his weight.
- If she is *price-oriented*, she selects the Host with the lowest price \( p \) in \( H_r \).

Finally, she visits this accommodation and she writes a review. The review is stored as a grade which value depends on the similarity between the price paid and the quality she has observed. This quality \( q^* \) is drawn from the normal distribution \( \mathcal{N}(q, \sigma) \) with \( q \) being the real quality and \( \sigma = \frac{2^{x/\sqrt{\nu}}}{\nu} \) with \( 1/\sqrt{\nu} \) being the standard deviation of \( U(0,1) \) and \( \nu \) being the number of accommodations visited in the past (initial value is 1). The grade is \( M_{h,t} = \begin{cases} 0 & \text{for } q^* < p \\ 1 & \text{for } q^* \geq p \end{cases} \) (0 means ‘unsatisfied’ while 1 means ‘satisfied’).

Once this process is over, the Hosts have the opportunity to adjust their price: either upward for the Hosts who have a match at this step or downward for those who don’t. The probability to adjust the price is

\[
Prob(\text{adjust price}) = \frac{m}{\ln(a)} \times \varepsilon
\]

where \( a \) (initial value is 1) is the number of past price adjustments, \( \varepsilon \) is the energy of the system, i.e. a parameter to control the frequency of actions in the simulation. The variable \( m \) depends on the Host’s strategy: *occupancy-oriented*, i.e. the grades have no influences on the Host’s decisions, the only thing that matters is the number of hosted Guests; *occupancy-and-satisfaction-oriented*, i.e. receiving a bad grade \( (M_{h,t} = 0) \) is a failure equivalent to not hosting a Guest at all. Table 1 shows how \( m \) is computed.

The repartition between Hosts and Guests depends also on the energy of the system \( \varepsilon \) (\( 0 < \varepsilon \leq 0.5 \)). In this case, it influences how often a Guest will make an action, based on \( P = H + G = \varepsilon P + (1 - \varepsilon)P \). Together with its influence on price adjustment, \( \varepsilon \) affects the speed of change in the simulation. Smaller [higher] \( \varepsilon \) will produce similar results but more slowly [quickly].

For readability, we run the simulations with all the agents in a category following the same strategy. Hence we generate four cases described in Table 2.

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2 We assume that the users – whether they are price- or quality-oriented – follow the same procedure to allocate a grade. The platform provides the same form to each customer for reviewing. And, even if the platform orientates the form to be focused on quality, we assume that customers assess the quality relatively to the price.
Table 1. Computation of $m$, using information accumulated since the last adjustment

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Action</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Reduce price (no Guest at this step)</td>
</tr>
<tr>
<td>Occancy-and-satisfaction-oriented</td>
<td>$m = \text{number of steps without Guests or positive reviews}$</td>
</tr>
<tr>
<td>Occancy-oriented</td>
<td>$m = \text{number of steps without Guests}$</td>
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<tr>
<td></td>
<td>Increase price (Guest at this step)</td>
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<tr>
<td></td>
<td>$m = \text{number of positive reviews}$</td>
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</tbody>
</table>

| Table 2. Strategies and scenarios

<table>
<thead>
<tr>
<th>Guests</th>
<th>Quality-oriented</th>
<th>Price-Oriented</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Case 1</td>
<td>Case 4</td>
</tr>
<tr>
<td>Hosts</td>
<td>Occupancy-and-satisfaction-oriented</td>
<td>Case 1</td>
</tr>
<tr>
<td></td>
<td>Case 2</td>
<td>Case 3</td>
</tr>
</tbody>
</table>

In order to show how the characteristics of agents influence their success and behavior on this market, we show the results per subset of agents of similar characteristics. Concretely, the Hosts are ordered based on the quality of their accommodation ($q$) and separated into 10 groups (the 9 cutting points corresponding to the “deciles” of $q$’s distribution): the first [last] group represents the Hosts with the lowest [highest] $q$. The same principle is applied to the Guests, based on their reservation price ($r$): the first [last] group represents the Guests with the lowest [highest] $r$. Since these characteristics are fixed for each agent during the whole simulation, the deciles and the groups are stable. In the following, we show the results of the interesting variables based on these groups.

4 Results

The results discussed below are based on the following parameters: population $P = 1000$, energy $\epsilon = 0.25$, Hosts’ population $H = 250$, Guests’ population $G = 750$, cognitive ability $\alpha = 10$. The results are recorded at $t = 1000$ steps and
they show the average over 20 repetitions of the simulation with different initializations of the agents.

We start by discussing the Case 1. Fig. 1 shows the Hosts’ average margin (i.e. the difference between price $p$ and quality $q$) and $P$ itself. We observe a limited margin, i.e. a rather strong alignment between $p$ and $q$. The Hosts have almost found the ‘right’ price regarding their quality. The only exceptions lie on the extremes, due to the behavior of Guests: because they look for accommodations below their reservation price ($r$), they create a stronger demand on the cheapest accommodations making it possible for those Hosts to offset the bad reviews. On the other side, the high-end accommodations appeal only a very small fraction of Guests (because these high-$r$ Guests may prefer a cheaper option anyway). In order to increase occupancy, those Hosts have to value their accommodations below their actual quality (and, therefore, their ‘right’ price). We see on Fig. 2 how the Guests with the lowest $r$ suffer from the competition on the cheapest accommodation by not finding a match. At the same time, because $p$ and $q$ are well aligned, the satisfaction of finding accommodations with $q \geq p$ is relatively limited, except for the Guests with the highest $r$ who benefit from the limited appeal of high-end accommodations. This is coherent with Fig. 3 where we see again how the Guests with the lowest $r$ are hardly able to find a match. For comparison, we can calculate the expected maximum number of reservation that a Guest can make during a simulation with $\frac{\mu}{\sigma} \times t = \frac{\epsilon p}{1-\epsilon} \times t = \frac{0.25}{0.75} \times 1000 = 333$ in this case. Similarly, on Fig. 4 showing the expenses related to these reserved accommodation, we observe the clear correlation between $r$ and the average cumulated contribution of Guests to this market.

In Case 2, by removing the interest of Hosts in Guests’ satisfaction, the simulation generates a rather different situation. Except for the two highest subgroups of Hosts, the Hosts’ margins are much higher, excluding de facto almost 50% of the Guests. However, the revenue generated by this market is still high, due to the highest price, making this strategy rather rewarding for Hosts. The evolution comes from the incentives of cheaper Hosts to increase their prices as long as they can attract Guests with higher $r$. At the same time, this evolution is limited by the past reviews of Guests, keeping a certain correlation between $q$ and $p$: between two Hosts with the same $p$, Guests will prefer the one with the highest $q$, based on how the Host was satisficing in the past. This emphasizes the difficulty for Guests to choose wisely, when they do not know what was the price paid by the past reviewers.

In Case 3, the Guests are only interested in getting the cheapest accommodation, within the range delimited by their $r$. Interestingly, all the Hosts converge to the same price, since the Guests will always prefer the cheapest option, no matter how the quality is. Hence, the most expensive accommodations are systematically avoided (and, therefore, reduce their price), while the cheapest accommodations have a clear incen-

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3 Other parameter values have been tested to guarantee the robustness of our results: the results are collected once the platform has stabilized (large $t$); $\epsilon$ and $c$ do not affect the relative results of the scenarios; population size ($P$) is meant to guarantee the alignment between $p$ and $r$ based on random draws (a smaller $P$ increases the chance of shortage on either side of the platform, such an interesting outcome is beyond the scope of this paper).
tive to increase their price. The equilibrium is then at $p = 0.5$. The global result is that all the Guests with $r \leq 0.5$ are excluded from this market and the total revenue of this market is relatively low.

In Case 4, the Hosts with a lower $q$ have an additional incentive to reduce their price by comparison with Case 3. These decisions lead the whole market to an even lower price. In return, there is a larger percentage of satisfied Guests, by comparison with all the other cases. However, this strategy is still detrimental for the revenue on this market.

**Fig. 1.** Hosts’ perspective - Margin and price. The left axis shows the average margin of Hosts in each subgroup (bars). The right axis shows the average price of accommodations in each subgroup (dots).

**Fig. 2.** Guests’ perspective – Matching and Satisfaction. The bars show the percentage of unmatched, unsatisfied and satisfied Guests within each subgroup.
Discussion

The decentralized learning and coordination favored by customer reviews have very contrasted results depending on the behavior of agents. Even if our results involve agents with similar behaviors, they give us some clear insights about how the owners could influence the behaviors on their platforms (in particular, to avoid such extreme scenarios). We address this question by using a game theory framework where the quality-oriented [price-oriented] guests and satisfaction-oriented [occupancy-oriented] hosts are the cooperative [individualistic] players. By doing so, we obtain almost a prisoner dilemma where cooperation is dominated by individualism, at least from the host perspective. Case 1 being the cooperation-cooperation scenario, hosts have a clear incentive to ignore the satisfaction of guests, leading them to behave as in Case 2 where the reduction of visits by guests is compensated by the highest price charged. For the same reasons, they would prefer Case 3 over Case 4. The interest of guests is less monolithic, due to the trade-off between satisfaction (for the subgroups with a higher r) and exclusion (for the subgroups with a lower r). However in the dominant scenario of individualistic hosts, one can imagine that guests would prefer Case 3 over Case 2. This individualistic-individualistic scenario is the worst solution for all the agents (except for guests with the highest r).
Consequently, a platform policy supporting a sense of community and cooperation (Case 1) needs to be strongly promoted, if one tries to oppose the individual interests of the participants which would lead them to adopt a non-cooperative behavior (Case 3). Of course, the sharing economy is based on ethical and cooperative behaviors and the permeability between agent categories makes it easier for them to understand the expectations of the other side. The platform owner can also have their own objectives which would influence the orientation of policies. For instance, an owner interested in attaining a critical mass of participants or getting fees per transaction would orient its policies towards Case 1. On the contrary, an owner getting the same fees but willing to reduce the costs related to an increased activity on the platform might favor Case 2.

The evolution happening in Case 2 questions the necessity of policies beyond the platform. The hypothesis made here (i.e. customers keep coming even if their satisfaction is very low) may seem extreme. However, assuming that the sharing economy provides goods to individuals who cannot afford transactions on regular marketplaces, we see here the emergence of an overpriced low-end market. By giving more options to individuals who were excluded from those marketplaces, the profit-based sharing economy challenges many markets (see for instance the reactions against Airbnb or Uber in many cities). At the same time, it can produce its own failures by excluding or overcharging its participants. Moreover, the early stage of the market has a strong influence on the future evolution of the product and customer base. Excluding some categories (of products or customers) will affect the future attractivity of this market regarding these categories, via a snowball effect.

6 Conclusion

Using an agent-based model mimicking the emergence of a profit-based platform for sharing consumer goods, we have shown how much this type of sharing economy should emphasize cooperative behaviors more than profit incentives. For platform owners and policy makers, this model can help in two directions: if the market evolution is observable, we can estimate the behavior of agents or, reciprocally, if the behavior is known, we can predict the evolution of the market. In this paper, we have focused on the second direction, while improving the first direction would be a strong incentive to monitor the evolution of these platforms (in terms of user characteristics, price distribution and so on).

Our next stage will be to introduce entry and exit into the model, in order to study the reinforcing dynamics happening on these markets as well as their potential for phase transitions or cycles (e.g. gentrification of customers, strong instability or network effects, for instance). By this way, we will extend our present analysis in terms of sustainability of this type of platforms and as a mass market rather than a niche market. Besides, in the dynamic version of the model, by influencing the population evolving on the market, individual decisions on the supply side will have evolving collective outcomes. Equally, such a model would help platform owners in understanding how they should limit or encourage the entry of certain categories of suppliers to alter competition (i.e. orientate the prices of some categories of suppliers). By
doing so, they would be able to facilitate the realization of objectives (platform objective of attractivity, supplier objective of profitability or customer objective of saving).

References