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Effect of technological breakthroughs on electronic markets

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Abstract Electronic markets have profoundly affected competition and market structures. Many authors have argued that electronic markets can promote competition and increase allocational efficiency, primarily by reducing buyer and seller search costs. However, conventional competitive models do not explain several phenomena we actually observe in electronic markets. Consequently, a variety of researchers have introduced complications to the basic competitive search model, including asymmetric information, branding and product differentiation, network effects, and agency considerations in order to explain e-commerce behavior. However, most previous studies neglect the fact that such characteristics may reflect underlying market evolution processes. Depending upon the evolutionary pattern of a market, the behavior and performance of markets differ. In this paper, we construct a model to examine e-commerce in the framework of dynamic market evolution. Using a system of replicator dynamics, we split a market into two distinct parts and show that the competition within the two segments will follow different, though interrelated evolutionary patterns. We supply the conditions for the existence of a unique global stable equilibrium in this dynamical system. Our model suggests that exogenous increases in online customers triggered by technological breakthrough often play more important roles than price differentials in determining the evolutionary path of a market. By emphasizing the

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short term disequilibrium along the market evolution path, our study complements the competitive equilibrium view of electronic market.

Keywords Electronic markets · E-commerce · Evolutionary game theory · Dynamical system · Market evolution · Technological breakthrough · Dynamical equilibrium

1. Introduction

Since 30 April 1993, when CERN[1] announced that anyone could use its World Wide Web protocols without paying a fee, electronic commerce (e-commerce) on the Internet has grown explosively. By 2004, more than 220 million Americans were expected to be online [3], consumer-oriented e-commerce in the United States exceeded $90 billion [29] and its growth rate was five times greater than that of conventional bricks-and-mortar sales [3]. Already, this energy has turned several markets upside down (witness the demise of many travel agents and the challenge of Amazon.com to conventional book stores) and it has created new means for buyers and sellers to interact (eBay.com claimed more than 90 million registered users in mid-2004). It is apparent that e-commerce[2] is having a profound impact on current market structures [6, 7, 21].

Nonetheless, there have been several bumps in the e-commerce road. First, many consumers either refuse to utilize Internet-based e-commerce [19], or they distrust the parties involved in e-commerce [23]. Second, many e-commerce firms have yet to find a way to become profitable, at least by conventional accounting standards [31]. Third, some conventional bricks-and-mortar firms experience "channel conflict" such that their e-commerce sales reduce their sales at their bricks-and-mortar outlets. Related to this, there exists the possibility of "free riding" in e-commerce whereby consumers utilize bricks-and-mortar stores to examine and test goods and then make their purchases for the lowest possible price on the Internet. Of course, the reverse can also be true—consumers use the Internet to gather information about goods such as automobiles, but then make their purchases at bricks-and-mortar locations.

Suffice it to say that the evolution of e-commerce has not been a linear and predictable phenomenon. What is apparent is that there is interaction between e-commerce market structure and the actions of e-commerce firms. Market structure affects firms' behavior, even while firms' actions influence and mold market structure. Thus, there is value in investigating the dynamic process of electronic market evolution.

[1] The acronym CERN represents the world's largest particle physics laboratory, the European Organization for Nuclear Research. Tim Berners-Lee, a CERN researcher, wrote a program to allow scientist to communicate easily with each other. It consisted of a language (HTML), a procedure for moving between files (HTTP), and an address protocol (URL). He eventually labeled this the World Wide Web.

[2] Note that e-commerce is a broad term that includes both electronic business transactions undertaken independent of the Internet (e.g., a withdrawal from a local bank ATM) and electronic business transactions undertaken via the Internet (e.g., a purchase of a PC via the Gateway.com Web site). Our focus here is on Internet-enabled e-commerce, but we should not forget that non-Internet electronic commerce has been taking place since World War I.

We adopt a system of replicator dynamics to describe evolutionary processes in Internet-based e-commerce. The replicator dynamics used in our model is a standard tool in analyzing evolutionary models (of course, we have the flexibilities to define subpopulations and their payoffs for this particular replicator dynamics). As a continuous time evolutionary selection mechanism, replicator dynamics was first studied in [30]. However, its name was formally introduced five years later by [28].[3] It is widely used to describe population evolution in biology and game theory [11, 24]. Although considered as a complex nonlinear dynamics, it is nothing more than a continuous time version of Darwin's theory of evolution. In fact, it is often equivalent to Genetic algorithm based reproduction processes. Weiball [34] gives an elegant proof that shows the mathematical relationship between replicator dynamics and the standard Darwinian reproduction function. The underlying assumption of the replicator dynamics is that each subgroup's "survivability" is proportional to its relative fitness in the whole population. As is true in biology and game theory, we assume behavior is shaped by trial and error. Hence, individual learning and adaptation influence many evolutionary processes.

Population dynamics theory also has reshaped classical game theory's frequent assumption of strict rationality. The result, often termed evolutionary game theory [34], provides intellectual sustenance for our replicator dynamics model, as does Reinhard Selten's Principle of the Trembling Hand. Both extend the tradition of bounded rationality doctine. Mailath [20] provides an excellent review of the previous literature in this area.

Recent empirical evidence concerning the Internet provides impetus for our modeling. Koch [15] noted numerous circumstances when higher, not lower, prices result when consumers purchase items on the Internet. The oft-noted phenomenon of "auction fever" provides but one example. Koch and Cebula [16] discuss how the Doctrine of "One Price" is routinely violated on the Internet and note that price dispersion there is usually greater than in bricks-and-mortar markets. They summarize evidence showing that price discrimination is endemic on the Internet, not the least because of prolific "data mining" by firms who collect detailed information about consumers and then utilize those data to set differential prices. Similarly, [4] report that, even after controlling the effect of flight ticket differentiation, substantial price dispersion exists in the online air travel market that is theoretically supposed to be highly efficient.

The implication of this evidence is that e-commerce markets will not necessarily yield competitive results, or imitate Bertrand competition,[4] even if search costs decline dramatically. Market imperfections will persist in e-commerce markets, at least in the short run. We demonstrate that this evidence is not an aberration because technological breakthroughs may temporarily change patterns of market evolution. We also show these circumstances can lead to the overestimation of online business's long run advantages over the traditional business.

[3] Replicator dynamics resemble chaotic systems in that both are complex nonlinear dynamic systems. However, the similarity stops here. Chaotic systems (especially high dimension ones) are almost unpredictable. That's why they are often compared to random walk or geometric Brownian motions. Replicator dynamics, on the other hand, is deterministic and highly predictable. Of course, real world evolution always involves noisy (e.g., mutation mechanism in Darwin's theory). Replicator dynamics do not use any mutation mechanism at all because evolutionary stability criteria are used to handle model robustness [34].

[4] In Bertrand equilibrium, zero-profit price clears the market (e.g., see [8]).

The rest of this paper is structured as follows: Section 2 describes our model based on population dynamics. We investigate some general characteristics of our dynamical systems in Section 3. The effects of technological breakthroughs on the market evolution are discussed in Section 4. Section 5 concludes paper with a summary of our research and fruitful directions for future research.

2. The model

We will use the market for airline tickets as an example to elucidate our model. However, our results can be easily extended to other market scenarios, though we note when our arguments are specific to the travel agent market.

There are two populations in our model, travel agents and customers. Each population can be further split into two sub-populations, online agents/customers and other agents/customers. Let $x_a^e, x_a^f \in [0, 1]$ be the percentage of online agents and other agents, respectively. Similarly, we denote $x_c^e, x_c^f \in [0, 1]$ as the percentage of online customers and other customers, respectively. Online customers interact with online agents, and offline customers interact with offline agents. Over time, each agent and each customer can learn from the results of his/her previous business interactions. Since each population only contains two subpopulations, it follows that $x_a^e + x_a^f = 1$ and $x_c^e + x_c^f = 1$. In the real world, it may be difficult to ascertain if a customer is an online or offline customer. However, it is immaterial to travel agents whether they deal with a customer drawn from a polymorphic population or instead a customer playing a mixed strategy by randomizing between online and offline booking. That is, we may interpret the population share of online customers as the probability that a customer will book her ticket online. Similarly, we can interpret those click-and-mortar ticket agents as mixed strategy players who sell flight tickets both online and offline. Of course, there are certain problems for this interpretation. For example, the mixed strategy payoff may be affected by the interactive dynamics between online and offline divisions in the real business world (e.g., channel conflicts and cannibalization). In general, this type of model setup is more appropriate for studying aggregate market evolutionary dynamics than for studying firm-level strategies (see [9] for further discussion). Next, we denote p_e and p_f as the prices offered by the two agent sub-populations. Since there are many flight agents in the market, the distributions of p_e and p_f are asymptotically normal under general conditions. That is,

$$p_e \overset{A}{\sim} N\left(\bar{p}_e, \sigma_e^2\right) \quad \text{and} \quad p_f \overset{A}{\sim} N\left(\bar{p}_f, \sigma_f^2\right).$$

Now, define the expected payoff of online and other agents in a given state $x(t) = [x_a^e(t), x_c^e(t)] \in \Theta$ as $u_a^e(x_a^e, x_c^e, \underline{D})$ and $u_a^f(x_a^e, x_c^e, \underline{D})$, respectively, and define the expected payoff of online and other customers as $u_c^e(\bar{p}_e, \sigma_e^2, \underline{D})$ and $u_c^f(\bar{p}_f, \sigma_f^2, \underline{D})$, where $\underline{D}$ represents the set of all other relevant exogenous variables. Note that if we treat $(\bar{p}, \sigma^2)$ as functions of $(x_a^e, x_c^e, \underline{D})$, we can rewrite customers' payoff functions as $u_c^e(x_a^e, x_c^e, \underline{D})$ and $u_c^f(x_a^e, x_c^e, \underline{D})$. All the payoff functions and subpopulation portions are common knowledge.

There are three central assumptions that influence the model.

1. *Many homogeneous agents and customers exist in each sub-population. The only factor differentiating agents/customers is whether they go online to sell/buy flight tickets.*[5]
2. *Travel agents and customers are able to learn via market evolution. Each has a tendency to adopt the strategy with higher expected payoff, thereby increasing their "fitness" in the population.*
3. *The expected customer/agent payoff functions have continuous first partial derivatives.*

We utilize a two-population replicator dynamics [34] to describe the evolutionary process of our market. Mathematically, the replicator dynamics of the agent population can be written as:

$$\dot{x}_a^e = \left[u_a^e\left(x_a^e, x_c^e, \underline{D}\right) - \overline{u}_a\left(x_a^e, x_c^e, \underline{D}\right)\right]x_a^e \qquad (1)$$

where $\overline{u}_a = x_a^e u_a^e + x_a^f u_a^f$ is the expected payoff of the whole agent population and $\dot{x}_a^e$ is the derivative of x_a^e with respect to t. Plug $\overline{u}_a$ into (1) and the equation can be rewritten as:

$$\dot{x}_a^e = \left[u_a^e\left(x_a^e, x_c^e, \underline{D}\right) - u_a^f\left(x_a^e, x_c^e, \underline{D}\right)\right]\left(1 - x_a^e\right)x_a^e \qquad (2)$$

This can be expressed as:

$$\dot{x}_a^f = \left[u_a^f\left(x_a^e, x_c^e, \underline{D}\right) - u_a^e\left(x_a^e, x_c^e, \underline{D}\right)\right]\left(1 - x_a^f\right)x_a^f \qquad (3)$$

Similarly the replicator dynamics of the customer population can be written as:

$$\dot{x}_c^e = \left[u_c^e\left(\bar{p}_e, \sigma_e^2, \underline{D}\right) - u_c^f\left(\bar{p}_f, \sigma_f^2, \underline{D}\right)\right]\left(1 - x_c^e\right)x_c^e \qquad (4)$$

and

$$\dot{x}_c^f = \left[u_c^f\left(\bar{p}_f, \sigma_f^2, \underline{D}\right) - u_c^e\left(\bar{p}_e, \sigma_e^2, \underline{D}\right)\right]\left(1 - x_c^f\right)x_c^f \qquad (5)$$

The expressions $x_a^e + x_a^f = 1$, and $x_c^e + x_c^f = 1$, plus Eqs. (2) and (4), are sufficient to describe our dynamical system. We now focus on the electronic market evolution process.

[5] This subpopulation homogeneity assumption is commonly used in the evolutionary theory. Of course, it may be too stringent when we study business strategies of a few competing firms. For example, some recent marketing science and industrial organization studies like spatial differentiation models have attempted to generalize competitive models with assumptions of agent homogeneity. However, most evolutionary models study market evolutionary path at the aggregate level. The model robustness gained through introducing player heterogeneity generally does not justify the significantly increased analytical complexity.

3. General characteristics of the model

In order to preserve generality, we assume the payoff matrix is time-dependent in our model. Without a predetermined payoff matrix, however, some of the results of evolutionary game theory are not applicable. Nonetheless, we can still obtain some intriguing insights into electronic market evolution from this general dynamical system.

Given our model of differential Eqs. (2), (4) and the state space Θ, the following questions naturally arise.

- Do solutions to the model exist?
- Do equilibria exist and, if so, how many?
- Are the equilibria stable?

We now discuss these questions one by one.

3.1. Existence, uniqueness and differentiability of solutions

Proposition 1. *For this two-population replicator dynamics model and a given set of exogenous variables $\underline{D}$, there is a unique solution $\xi(., x^0) : T \to \Theta$ through every state $x^0 \in \Theta$. Moreover, $\xi(1, x^0)$ is continuous and differentiable in $t \in T$ and $x^0 \in \Theta$.*

This proposition may be directly derived from Picard-Lindelof theorem and is based on Assumption 3 and Eqs. (2) and (4) of our dynamical system. As noted above, we here implicitly treat $(\bar{p}, \sigma^2)$ as functions of $(x_a^e, x_c^e, \underline{D})$.[6]

3.2. Existence and uniqueness of interior equilibria

Before we go further, we must provide a formal definition of dynamical equilibrium.

Definition 1. A dynamical equilibrium under a solution mapping ξ is a state $x \in \Theta$ such that $\xi(t, x) = x$ for alls $t \in R$. Or, equivalently, an equilibrium of a dynamical system $\dot{x} = \psi(x)$ is a state $x^* \in \Theta$ such that $\psi(x^*) = 0$.

Using this definition, it follows that there are multiple equilibria in our model. Four equilibria exist in degenerate cases: $x_a^e = 0, x_c^e = 0$; $x_a^e = 1, x_c^e = 0$; $x_a^e = 0, x_c^e = 1$; and, $x_a^e = 1, x_c^e = 1$. In these equilibria, some payoff functions cannot be meaningfully defined. Hence, we are more interested in finding the interior equilibrium. To do so, we note that the interior of a state space includes all the possible states that are not on the boundary of the state space [10, 11]. In our paper, the interior of the state space does not include the above stated four boundary states (equilibria).

The conditions for the existence of a unique interior equilibrium of our model are as follows:

[6] For a rigorous proof of Picard-Lindelof theorem, see [10].

Proposition 2. *There is a unique interior equilibrium of the two-population replicator dynamics if and only if there is only one state* $x^* \in \mathrm{int}(\Theta)$ *satisfying both* $u_a^e(x_a^e, x_c^e, \underline{D}) = u_a^f(x_a^e, x_c^e, \underline{D})$ *and* $u_c^e(\bar{p}_e(x_a^e, x_c^e), \sigma_e^2(x_a^e, x_c^e), \underline{D}) = u_c^f(\bar{p}_f(x_a^e, x_c^e), \sigma_f^2(x_a^e, x_c^e), \underline{D})$*, where* $\mathrm{int}(\Theta)$ *stands for the interior of the state space* Θ.

Proposition 2 is obtained by applying the Poincare-Hopf theorem (see [10] for a proof) to the replicator dynamics in our model. It suggests that the uniqueness conditions are not as restrictive as they might first seem. Intuitively, the uniqueness conditions require the existence of a single internal state where the expected payoffs of online and offline players are equal. As noted above, we wish to avoid unnecessary restrictions on the payoff functions and to make our model as general as possible. If a more specific dynamic system exists, then we can use Proposition 2 to determine if a unique equilibrium exists.

3.3. Stability conditions of the interior equilibrium

A dynamical equilibrium will possess desirable characteristics if it exhibits stability. Two types of stability are of concern: local stability and global stability.

Definition 2. A dynamical equilibrium $x^* \in \Theta$ is locally asymptotically stable if there is a neighborhood B of x^* such that $\lim_{t\to\infty}\xi(t, x^0) = x^*, \forall x^0 \in \Theta \cap B$.

We use this definition to support Proposition 3:

Proposition 3. *The dynamical equilibrium* $x^* \in \Theta$ *in our model is locally asymptotically stable if*

$$\left[\frac{\partial u_i^e(x^*)}{\partial x_i^e} - \frac{\partial u_i^f(x^*)}{\partial x_i^e}\right]\left(1 - x_i^{e^*}\right)x_i^{e^*} < \left(2x_i^{e^*} - 1\right)\left[u_i^e(x^*) - u_i^f(x^*)\right],\quad \text{where } i = a \text{ or } c. \tag{6}$$

Note that (6) guarantees that all Eigen values in the matrix $D\psi(x)$ are positive, a necessary condition for x^* to be locally stable.[7] However, since local stability usually does not ensure global stability, we need to specify conditions for global stability of an equilibrium.

Definition 3. An equilibrium $x^* \in \Theta$ is globally stable if $\lim_{t\to\infty}\xi(t, x^0) = x^*, \forall x^0 \in \Theta$.

Therefore, global stability implies local stability. However, global stability is a much stronger condition. The following theorem provides the necessary condition for the existence of a global stable state based upon the concept of Lyapunov function,

[7] Hirsch and Smale [10] provide a proof.

some real-valued continuous function constructed to prove Lyapunov stability. An equilibrium is Lyapunov stable if no small perturbation of the equilibrium state induces a movement away from it [34].

Theorem 1. *An equilibrium $x^* \in \Theta$ is globally stable if we can find a differentiable function $V : \Theta \to R$ such that $V(x^*) = 0$; $V(x) > 0$ and $\frac{\partial V(x(t))}{\partial t} < 0, \forall x \neq x^*$, where the function V is a Lyapunov function.*

Therefore, we need to find a Lyapunov function for our model if we want to prove that the equilibrium $x^* \in \Theta$ is globally stable. Unfortunately, there is no simple, general way to find Lyapunov functions. The problem of specifying the general payoff functions in our model to ensure the existence of a global stable state is beyond the scope of this paper.

We now shift our focus to the discussion of the general characteristics of our model based upon our still general assumptions. In the next section, we provide additional assumptions for our model and discuss the intriguing implications of the model.

4. The effects of technological breakthrough on market evolution dynamics

Net-based e-commerce came about because of significant technological innovations such as the World Wide Web, browsers and easily used encrypted payment mechanisms [1]. When such critical innovations occur, they often are accompanied by sudden exogenous increases in online customers. So the impact of technological breakthrough can be modeled as an exogenous shock that suddenly and unexpectedly increases the number of Internet users who buy flight tickets online. Because Assumption 5 already assumes a diffusion process of customers entering online marketplace, it must be pointed out that an expected technology improvement will not be considered a breakthrough if it is gradually achieved and thus has been fully built into the expectations.

We now define $x_c^e = {}_1x_c^e + {}_2x_c^e$, where ${}_2x_c^e$ represents the portion of online customers affected by exogenous technological shocks. It is worth noting here that an exogenous shock ${}_1x_c^e$ will not change the endogenous term ${}_2x_c^e$ instantaneously. Instead, it will gradually impact ${}_2x_c^e$ through the replicator dynamics. Now we can rewrite our dynamical system as:

$$\dot{x}_a^e = \left[u_a^e\left(x_a^e, x_c^e, \underline{D}\right) - u_a^f\left(x_a^e, x_c^e, \underline{D}\right)\right]\left(1 - x_a^e\right)x_a^e \quad (2)$$

and

$${}_1\dot{x}_a^e = \left\{u_c^e\left(\bar{p}_e\left(x_a^e, x_c^e\right), \sigma_e^2\left(x_a^e, x_c^e\right), \underline{D}\right) - u_c^f\left(\bar{p}_f\left(x_a^e, x_c^e\right), \sigma_f^2\left(x_a^e, x_c^e\right), \underline{D}\right)\right\}\left(1 - x_c^e\right)x_c^e \quad (7)$$

$$x_c^e = {}_1x_c^e + {}_2x_c^e \quad (8)$$

Now the two-population replicator dynamics can determine that $\dot{x}_c^e$ and ${}_1\dot{x}_c^e$, and ${}_2\dot{x}_c^e$ and are exogeneous to our model. We can obtain additional insights into our modified dynamical system by adding four additional assumptions.

4. *There exists a unique globally stable interior equilibrium* $x^* \in \Theta$ *in the dynamical system given by Eqs.* (2) *and* (4).
5. *In the absence of any exogenous disturbance, we assume* $\dot{x}_i^e > 0$ *and* $\ddot{x}_i^e < 0$ *where* $i = a$ *or* c. *Denote the difference between the average prices in the two market segments as* $\Delta\bar{p} = \bar{p}_f - \bar{p}_e$ *such that* $\lim_{t\to\infty}\Delta\bar{p} = 0$.
6. $\frac{\partial \bar{p}_e}{\partial_2 x_c^e} > 0$, $\frac{\partial \bar{p}_f}{\partial_2 x_c^e} < 0$; $\frac{\partial \sigma_e^2}{\partial_2 x_c^e} > 0$, $\frac{\partial \sigma_f^2}{\partial_2 x_c^e} < 0$; $\frac{\partial u_a^e}{\partial_2 x_c^e} > 0$, $\frac{\partial u_a^f}{\partial_2 x_c^e} < 0$.
7. u_c^i *monotonically decreases in* $\bar{p}_i$ *and* σ_i^2, *where* $i = e$ *or* f.

Approximately 60 percent of all Americans have online access in their home or place of work, up from 25 percent in 1995 [12]. The same report, however, indicated that 42 percent of Americans say they do not use the Internet and 24 percent are truly offline in that they have no direct or indirect experience with the Internet. These latter individuals have no choice but to book their tickets through traditional agents. It is reasonable to attribute some proportion of the increase of the online customers to unanticipated technological breakthroughs. Hence, we isolate ${}_2x_c^e$ from x_c^e and treat it as an exogenous variable. An exogenous increase in ${}_2x_c^e$ is used to characterize the impact of technological breakthroughs. Assumption 5 ensures that the average prices in the two market segments will converge to each other asymptotically.

There is an intuitive justification for Assumption 6. An increase in ${}_2x_c^e$ brings the e-commerce market more customers without changing the number of online agents in the very short run. Therefore, facing demand pressures, online agents tend to raise their ticket prices and fees to reap the benefits of exogenous positive demand shock. On the other hand, for traditional agents, competition becomes more intense since their aggregate market share has shrunk. As a consequence, the average ticket price and the price dispersion will go down. Following the same argument, the exogenous increase in x_c^e will benefit online agents while undermining traditional agents' profitability. Given these assumptions, we are now capable of describing the effects of exogenous technological shocks on the electronic market evolution.

Proposition 4. *Technological breakthroughs that cause exogenous increase of online customers' population share will expedite the expansion of online business. If the technological shock is big enough, it may change the sign of* $u_c^e - u_c^f$, *which will temporarily reverse the original market evolution direction in the customer population.*

The first part of this proposition can be derived from Assumption 6. Note that $\frac{\partial \dot{x}_a^e}{\partial_2 x_c^e} = [\frac{\partial u_a^e}{\partial_2 x_c^e} - \frac{\partial u_a^f}{\partial_2 x_c^e}](1 - x_a^e)x_a^e > 0$ since we know $\frac{\partial u_a^e}{\partial_2 x_c^e} > 0$ and $\frac{\partial u_a^f}{\partial_2 x_c^e} < 0$. Because we assume $\dot{x}_a^e > 0$ in Assumption 5, we know that technological breakthroughs will expedite the expansion on online business (x_a^e will increase at a faster rate). For the second part of this proposition, we now have $\frac{\partial u_c^e}{\partial_2 x_c^e} = \frac{\partial u_a^e}{\partial \bar{p}_e}\frac{\partial \bar{p}_e}{\partial_2 x_c^e} + \frac{\partial u_a^e}{\partial \sigma_e^2}\frac{\partial \sigma_e^2}{\partial_2 x_c^e} < 0$ and $\frac{\partial u_c^f}{\partial_2 x_c^e} = \frac{\partial u_c^f}{\partial \bar{p}_f}\frac{\partial \bar{p}_f}{\partial_2 x_c^e} + \frac{\partial u_c^f}{\partial \sigma_f^2}\frac{\partial \sigma_f^2}{\partial_2 x_c^e} > 0$. Thus, $u_c^e - u_c^f$ may turn out to be negative if the exogenous increase in ${}_2x_c^{e'}$ is sufficiently large, and it is easy to see $\dot{x}_a^e < 0$ under this condition.

In order to compare the competitive advantage of an online agent over traditional agents in a dynamic sense, we define the relative profitability (RP) of an online agent as follows.

Definition 4. The relative profitability of the on line agent at time t is: $RP(t) = \frac{u_a^e(t)}{u_a^f(t)}$.

Given our definition of relative profitability, we have the following proposition.

Proposition 5. *A technological breakthrough that causes an exogenous increase of online customers' population share will enhance the online agents' relative profitability in the short run. In the long run,* $\lim_{t\to\infty} RP(t) = 1$ *and* $\text{lim}t \to \infty \Delta \bar{p} = 0$ *even if technology breakthroughs cause exogenous shocks. In addition,* x_c^e *and* x_a^e *still converge to* x^*.

The first part of this proposition follows from the inequality derived from Assumption 6 such that $\frac{\partial RP}{\partial_2 x_c^e} = \frac{u_a^f \partial u_c^e - u_a^e \partial u_a^f / \partial_2 x_c^e}{(u_a^f)^2} > 0$. To justify the second part of this proposition, we rely upon Assumptions 4 and 5. We know that $\text{lim}t \to \infty RP(t) = 1$ and $\lim_{t\to\infty} \Delta \bar{p} = 0$ without exogenous disturbances. From the modified dynamical system of Eqs. (2), (7), and (8), it is clear that exogenous shocks on x_c^e will not cause any structural changes of this system if other exogenous variables in $\underline{D}$ remain unchanged. Moreover, x^* will still be the equilibrium in the long run since it is globally stable.

The results proved in Propositions 4 and 5 are qualitatively illustrated in Figs. 1–3. Figure 1 illustrates a market evolution path without technological shocks. It shows that market evolutionary forces will gradually reduce the price and profitability differences between the online and offline segments. Figure 2 depicts the result of an exogenous technological shock, per our model. It demonstrates how a strong demand-side shock can temporarily boost online ticket sale prices and online agents' profitability. However, it also shows that, as long as the structure of the replicator dynamics is intact,

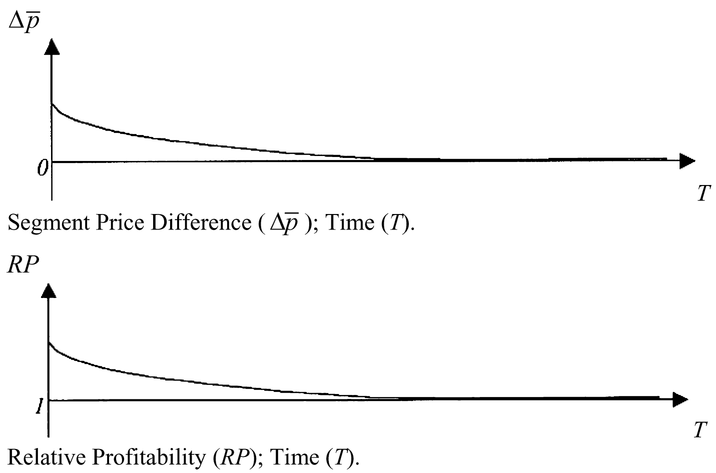


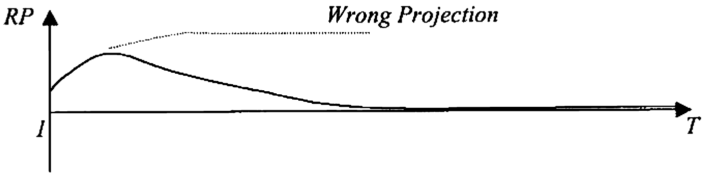
Fig. 1 Evolution of electronic markets without technological shocks

Segment Price Difference ($\Delta\bar{p}$); Time (T).

Relative Profitability (RP); Time (T).

Fig. 2 Evolution of electronic markets with a technological shock at t^*

Segment Price Difference ($\Delta\bar{p}$); Time (T).



Relative Profitability (RP); Time (T).

Fig. 3 Evolution of electronic markets with persistent technological shocks

the price and profitability differences will be eventually eliminated in the long run. The contrast between the paths illustrated in Figs. 1 and 2 can explain some recent empirical evidence. Product prices in an online market, for example, likely will be higher than prices in a traditional market after an exogenous technological shock. Moreover, price variations in the electronic market may not necessarily go down after the technological shock. In some cases, the price variability may increase as some online agents raise their ticket and fee prices to reap the short-term profits resulting from the positive demand shock in their e-commerce market. This is consistent with the empirical evidence reported in [4].

Given the frequency of technological innovation in e-commerce, it is useful to illustrate market evolution paths under a scenario of persistent technological shocks. Figure 3 depicts a possible market evolution path under this circumstance. It shows that online agents can maintain their prices and profitability at higher levels relative to traditional agents during the early stages of the market evolution. However, the advantages generated by persistent technological breakthroughs will disappear as time passes. This occurs because nearly all agents facing persistent technological breakthroughs will be able to adjust their behavior through learning and adaptation. Therefore, the window of opportunity to ticket sellers provided by technological shocks is only temporary and disappears in the long run.

In addition, persistent technological breakthroughs may cause online agents to overestimate the advantages they enjoy in the early stage of the market evolution. Therefore, boundedly rational managers and investors may believe that their current advantages are sustainable in the long run (shown as a wrong projection in Fig. 3 by dotted lines). They may hold this view for a variety of reasons, but among them is the anchor-destroying impact of persistent technological shocks [27]. It is Toffler's *Future Shock* [32] writ large such that accelerating change causes individuals to lose their conventional points of reference. Porter [22] also emphasizes this type of market informational problems: "*Companies that have deployed Internet technology have been confused by distorted market signals, often of their own creation. . . . In the early stages of the rollout of any important new technology, market signals can be unreliable. New technologies trigger rampant experimentation, by both companies and customers, and the experimentation is often economically unsustainable. As a result, market behavior is distorted and must be interpreted with caution.*" Therefore, we believe that a natural consequence of illusory projections generated by rapid technological change can be overinvestment in online business.

An interesting collateral question meriting discussion is how fast actors (in this case, travel agents) react to an exogenous demand shocks. If the adjustment of agents is sufficiently rapid, the impact of the technological shock on the market evolution will be mild and will not last long. However, in electronic marketplaces, firms often are surprisingly rigid. Bakos [2] argues that electronic markets typically require sizable capital investment in hardware, software, employee training and organizational transformation. Entry barriers may be substantial and uncertainty pervasive. These factors militate against quick reactions. In addition, switching costs may be large and this will lend inertia to both firms and consumers.

It is sometimes argued that first mover advantages exist in the electronic markets even though there are numerous examples of firms such as IBM and Microsoft that have prospered by imitating first movers (see Shapiro and Varian [25] for a balanced discussion). Network externalities [14], extensive economies of scale associated with digitization of information, and pervasive branding may produce advantages to firms that enter a market first or are the first competitor to exploit a particular technology. Our model suggests that the persistent technological breakthroughs also may favor first movers.[8] Even so, the model additionally suggests this advantage often is of a "here today, gone tomorrow" variety and can dissipate rapidly. Furthermore, this temporary advantage may not materialize at all if negative demand shocks also occur. In our model, ticket agents who adopt web technology earlier enjoy a first-mover advantage

[8] It is worth noting that the risks associated with new technology adoption, which have not been modeled in our paper, may significantly shrink the first-mover advantages. The risks mainly stem from the informational problems related to new technology adoption. Some of those informational problems are recently studied in the information technology adoption context [13, 17].

because of the positive demand shocks caused by potential technology breakthroughs. With such a positive demand shock, the market is in a temporary disequilibrium where online agents (early movers) could enjoy more pricing power because of exogenously inflated demand. That's why we may see significant price dispersion in such situations. Nevertheless, technological breakdowns (identity theft, major virus attacks, etc.) can suddenly reduce many customers' incentives to purchase their tickets online. Such technological breakdowns, if unexpectedly instigated, may significantly shrink the early mover advantage caused by technological breakthroughs.

5. Conclusions

In this paper, we construct a dynamic model to describe the electronic market evolution. The model suggests that technological shocks can enhance early mover advantages. Specifically, the early adopter travel agents who go online may benefit substantially from exogenous increases in their customer bases, while the competition in the traditional market will become increasingly severe as customers disappear. However, the window of opportunity closes as time passes. Based upon overenthusiastic and inaccurate projections, boundedly rational investors and business practitioners may suffer from the illusion that the advantages enjoyed by online business are sustainable. Thus, they tend to overestimate the long-term profitability and market share of online business during the early market evolution stage. This argument is consistent with the fact that market signals in the early stages of technology diffusion are unreliable and sometimes misleading [18, 22].

Our study makes several contributions to the extant literature on electronic market and Internet business. First, by adopting an evolutionary view of the electronic market, our paper provides a theoretical explanation of many empirical observations that are difficult to be justify with the competitive equilibrium view of the electronic market. Second, it underscores the severity of market distortion during the early stages of business implementation following major technological breakthroughs. Third, because boundedly rational market players tend to form erroneous expectations of business prospects, our study suggests that disequilibrium analyses (e.g., see [5]) should be used to investigate the impact of technological breakthroughs on short-term market dynamics. The main business implication of our study is that short-term business advantages solely caused by technological breakthroughs are usually not sustainable. It is certainly true that electronic market can dramatically improve business efficiency and reduce transaction costs, but like many other technological breakthroughs, it can only generate business advantages that will dissipate rapidly. Business strategies must be developed based upon the understanding that market evolutionary forces will soon or later correct disequilibrium caused by exogenous shocks.

Clearly, other factors not included in our model might influence the evolution of electronic markets. Some of these variables, for example, those relating to public policy on an issue such as Internet taxation, could turn out to be significant. These variables are capable of inducing structural change in our dynamical system. However, as [33] demonstrates in his review of catastrophe theory in dynamical systems, small changes in such variables usually will not result in radical changes in the qualitative nature of a dynamical system.

As an early attempt of applying evolutionary dynamics to study electronic marketplace, our study has several limitations. First, the technology diffusion process is given in Assumption 5, and it would be much better if the diffusion process could be endogenized in the model. Second, we argue that persistent technological breakthroughs may cause some agents to overestimate their advantages. However, we do not directly model this possibility of overestimation. An effort should be made in future studies to embed boundedly rational agents' expectations into our evolutionary model. Although there is a theoretical literature on the persistence of erroneous expectations (e.g., [26] empirical studies are certainly needed to further investigate how technological breakthroughs impact market participants' expectations. Such studies will test the robustness of our results and, more importantly, identify contextual factors that may exacerbate or alleviate the market distortion caused by technological breakthroughs. Third, we believe that future studies on the evolution of electronic market could yield more managerial insights if the heterogeneity of electronic business is incorporated the model. With the benefit of hindsight, we know that e-commerce companies with different business models and strategies had quite different fates in the market evolution. Considering this heterogeneity will further enhance our understanding of market dynamics and competitive separation along the evolutionary path of the electronic marketplace.

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