

# Which Product Will Survive To Be Standard?: Technology Adoption And The Role Of Governments

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## ABSTRACT

*While several surveys on technology diffusion have been undertaken, few attempts have been made to synthesize existing research to provide a framework for examining the role of governments. Is government intervention really required to remedy market failures caused by network externalities? This paper covers recent developments in this area, focusing on works in stochastic evolutionary game theory. We relate the results of equilibrium selections to the role of governments. JEL classification: L1, L53 Keywords: Path Inefficiency; Market Failure; Network Externalities*

## INTRODUCTION

In a market of several competing products, which product will survive to become the market standard? This question has been recognized as technology adoption in the presence of a network externality. Typical examples include the choice between VHS and Beta VCRs and the choice among video games such as PlayStation 2, Game Cube, and X-Box. Agents (or consumers) prefer to adopt a more popular technology (or product) in order to be able to share their technologies with other people. Software compatibility matters to consumers.

The literature has explored this topic since the seminal work of Katz and Shapiro (1986). A special issue of the *Journal of Economic Perspectives* (1994) has a literature review on this issue (Katz and Shapiro; Besen and Farrell; Liebowitz and Margolis). Among previous studies, Arthur (1989) is a pioneer work. Using a simple stochastic process, he illustrates how an inferior technology can potentially drive out a superior technology in the adoption process. Since the results depend on historical events, we are unable to predict the results *a priori*. The literature provides similar implications using more sophisticated stochastic models (Arthur, Ernoiev, and Kaniovski, 1987; Kaniovski and Young, 1995). Network externalities may cause a market failure as inferior technologies dominate the market. This problem is known as path-inefficiency.

The issue of path-inefficiency attracts the interest of economists. Does this market failure warrant government interaction? If so, this result can drive policy. For example, governments may promote R&D in the private sector, such as supporting research of one broadband system.

Few attempts have been made to synthesize existing research to assess the role of governments, although several surveys on technology adoption have been undertaken. We cover the development in this area, specifically focusing on recent works in the stochastic evolutionary game theory. Research regarding technology adoption has made great progress following the seminal articles by Foster and Young (1990), Kandori, Mailath and Rob (1993), and Young (1993) (Börger, 2001). Their analyses have been instrumental in integrating stochastic approximation theory and technology adoption in the presence of network externalities. However, sophisticated mathematical methodology has prevented proper attention from being given to the analysis. This paper introduces their works using a simplified description. We relate the results of equilibrium selections to the role of governments.

Kandori and Rob (1995, 1998) and Young (1998) are prominent works in this area. These authors reveal that the market selects socially desirable outcomes. Their analysis is distinct from previous works. In the standard argument, the utility of agents is increasing in the number of agents using the same technology. Kandori and Rob, and Young introduce erroneous decision-making by agents using the notion of mutations or errors. Some agents choose a technology randomly. The notion incorporates the situation where agents are not familiar with market conditions. In a dynamic technology adoption process, mutations or errors make it possible for a lagging but superior technology to catch up to a popular but inferior technology. Pareto efficient market outcomes are the result. In this case, the results imply no role for government intervention.

Despite these appealing results, we should be careful in applying the analysis to real world industrial policies. It may take very long for the market to attain a stochastically stable equilibrium. The analysis does not answer questions regarding the speed of convergence in the technology adoption process. Government intervention may be desired to promote the adjustment process. This situation is analogous to policy debates between New Classicalists and Keynesians in Macroeconomics. Keynesians suggest utilizing government intervention in order to resolve disequilibrium, such as unemployment, in the short-run. The main body of evidence provided by Kandori and Rob and Young, that a Pareto efficient outcome will emerge with bounded rational agents, is a breakthrough. However, the models are by no means complete. We conclude the paper with citations of the analysis' possible restrictions, referring to findings in other studies (Cowan, 1991; Amable, 1992; Ellison, 1993; Karshenas and Stoneman, 1993; An and Kiefer, 1995; Stoneman and Kwon, 1996; Dalle, 1997).

## STOCHASTIC EVOLUTIONARY GAMES

### Nonergodicity Process

Arthur (1989) provides a few features about technology adoption when network externalities are present. He illustrates the possibility that an inferior technology, (which leads in popularity for some reason), may drive out a superior technology and survive to become the standard. Let us start with the overview of his model. His seminal work operates as a benchmark in the following discussion.

Two unsponsored technologies, A and B, are competing for potential adopters. There are two disjointed groups of agents in population, R and S. These groups have heterogeneous tastes. Agents are randomly selected from the population, one by one, and choose one of the technologies. The order is a random process. Each type of agents is equally likely to be chosen at each time. Agents prefer a popular technology due to network externalities. A popular technology provides some convenience to agents; they can share software for the same hardware. When making decisions, agents know the number of past adopters of the technologies. Their decisions are irrevocable.

The situation is modeled using the expected payoff matrix in Table 1. Denote  $n_a$  and  $n_b$  as numbers of previous adopters of each technology, A and B. There are four constant variables. Assume that  $r > 0$ ,  $s > 0$ ,  $a_r > b_r$ , and  $a_s < b_s$ . Agent R obtains  $a_r + rn_a$  if s/he chooses the technology A. The inequality,  $a_r > b_r$ , implies that the agent R prefers technology A to technology B. Similarly, the inequality,  $a_s < b_s$ , implies that the agent S prefers technology B to technology A. An agent's utility is increasing in the number of agents using the same technology. Two positive constants,  $r$  and  $s$ , represent the degree of network externalities. Agents are apt to choose a more popular technology if the effects of network externalities dominate the effects of their preference. This means that, for example, agents choose to buy a Windows computer rather than a Macintosh computer despite their preference for Macintosh, if there are more Windows users than Macintosh users in the market.

Figure 1 illustrates a process of technology adoption. The label  $d$  in the y-axis is the difference in numbers of previous adoption of the two technologies,  $n_a - n_b$ , when  $n$  agents make decisions (in the x-axis). A positive (negative)  $d$  means that technology A is more (less) popular than technology B. The solid wave represents the

adoption process of technologies. The figure illustrates a case where technology A is initially more popular than technology B but technology B eventually catches up and dominates the market.

The lock-in process of technology B is explained using the concept of absorbing barriers. An absorbing barrier is the level of market dominance, where the effect of a technology’s network externalities dominates the effect of an agent’s preference toward the other technology. If the adoption process crosses either absorbing barrier, one technology dominates the market and the other technology disappears from the market. Both types of agents keep choosing the same technology.

The dotted horizontal lines in Figure 1 are the absorbing barriers ( $\Delta_s$  and  $\Delta_r$ ) for each technology, A and B. For example, although the agent R prefers technology A to technology B, the agent will switch his choice from A to B if technology B dominates a certain level of the market,  $\Delta_r$ . Hereafter, technology A is no longer chosen and, consequently, disappears from the market. The situation is described by the inequality,  $d = n_a - n_b < -\frac{a_r - b_r}{r} = \Delta_r$  (or equivalently  $a_r + rn_a < b_r + rn_b$ ). The analysis captures agents’ inconvenience from the use of a less popular technology. For example, agents cannot share PlayStation 2’s software with Xbox users (and vice versa). As a result, an unpopular technology will disappear from the market. Similarly, once technology A dominates the significant level of the market, agent S will switch her choice from technology B to technology A, despite of her preference for B over A. The inequality,  $d = n_a - n_b > -\frac{a_s - b_s}{s} = \Delta_s$  (or equivalently  $a_s + sn_a > b_s + sn_b$ ), describes the situation.

In the example, technology adoption is dependent on historical events. A technology, which leads with popularity for some reason, survives to be standard. Such an evolutionary process is nonergodic.<sup>1</sup> Nonergodicity creates the possibility of inefficient market equilibria. In the present case, an inferior technology may drive out a superior technology. David (1985) provides empirical evidence. The technologically inferior QWERTY keyboard was in competition with a superior keyboard, Dvorak. It was the QWERTY keyboard that survived to become the market standard. When network externalities lead to inferior technologies dominating the market, the problem is known as path-inefficiency. The market outcome depends on the adoption process (i.e., history). Hence, outcomes cannot be predicted *a priori*.

The literature has derived similar implications using more sophisticated models (Arthur, Ernoiev and Kaniovski, 1987; Kaniovski and Young, 1995). One technology dominates the market. However, there is no guarantee that a superior technology will be selected in the technology adoption process.<sup>2</sup> The results imply that the market mechanism may not work in the presence of network externalities. Externalities cause market failures. This is a familiar result of new classical economics. A policy question is whether government intervention can remedy the market failures.

Arthur (1989) illustrates how governments are powerless in preventing market failures. Suppose that technology A is superior to technology B (i.e.,  $r > s$ ). The government gives a subsidy,  $g$ , to A, and levies a lump sum tax,  $t$ , on B. Table 1.2 shows the new payoff matrix. The policy encourages the adoption of technology A and deters use of technology B. However, the government cannot prevent the lock-in of the inefficient technology B, as is shown in Figure 1. The current absorbing barriers shift to  $\Delta_r'$  and  $\Delta_s'$ :  $\Delta_s' = -\frac{a_s + g + t - b_s}{s} < -\frac{a_s - b_s}{s} = \Delta_s$  for technology A and  $\Delta_r' = -\frac{a_r + g + t - b_r}{r} < -\frac{a_r - b_r}{r} = \Delta_r$  for technology B. Even after the shift, absorbing barriers remain.

<sup>1</sup> An ergodic process means that “its long-run statistical behavior is essentially independent of the path taken, and in particular is independent of the initial conditions (Young, 1998, p.10).” More formally, a Markov process is ergodic if an asymptotic distribution  $\bar{\mu}(z | z^0) = \lim_{t \rightarrow \infty} \mu^t(z | z^0)$  is independent of an initial state  $z^0$ , where  $\mu^t(z | z^0)$  is an empirical distribution (or frequency) when a state  $z$  is visited during first  $t$  periods.

<sup>2</sup> A non-evolutionary game approach reaches the same conclusion of path-inefficiency (e.g., Amble, 1992).

Government intervention may help to delay the lock-in of an inefficient technology, but government intervention does not alter the results of technology adoption. The implication here is different from that of the new classical economics, where governments can internalize externalities in zero transaction cost situations.

**Ergodic Process**

Non-ergodicity limits the analysis of technology adoption. We cannot predict long-run market equilibrium. Equilibrium varies depending on the adoption processes (or history). An inefficient equilibrium could result since an inferior technology may survive and become standard. However, more recent studies provide different results. In these more recent studies, technology adoption is independent of history. The market selects a Pareto efficient equilibrium. Let us examine what causes the differences in outcomes by referring to prominent works in this area.

Ergodicity is attractive property. A technology adoption process will result in one of technologies being adopted independent of initial states. Kandori and Rob (1995, 1998) obtain the property by introducing two concepts, mutation and a long-run equilibrium (LRE). Mutation implies erroneous decision-making by agents. Agents maximize their expected payoffs, yet mutant agents select a technology based on different principles, such as a random choice. Mutants are not maximizing expected payoffs as standard agents do. Mutation incorporates minor, yet possible, mistakes by agents in the decision making process. Such errors are possible if agents do not have complete information regarding which technology predominates in the market. Mutation also incorporates the idea of entrepreneurs. Entrepreneurs seek new and potentially better technologies despite their short-run costs (Schumpeter, 1942). Contrary to Arthur’s model, where agents have complete information and never make mistakes, mutations create a framework where lagging technologies can catch up to a popular technology. Technological innovation progresses as time passes. Kandori and Rob’s model allows a new, superior, technology replace an old, inferior, technology, despite the fact that the former enters the market later. The contribution of their model is the inclusion of the long-run equilibrium concept. Mutants’ decisions perturb the technology adoption process. LRE is a state, which is not upset by the repeated perturbation of mutations. LRE guarantees the stability of the equilibrium.

Let us outline Kandori and Rob’s model. This clarifies what their analysis intends to remedy. An agent is chosen randomly from a finite population,  $M$ . The agent selects one technology from  $n$  alternative technologies. Let a state be represented by  $z = (z_1, \dots, z_n)$ , where  $z_i$  is the number of agents choosing technology  $i$ . We denote the payoff for the agent who chooses technology  $i$ , when other agents choose technology  $j$ , as  $u_{ij}$ . The expected payoff for an agent choosing technology  $i$  is:

$$\Pi_i(z) = \frac{1}{M-1} [\sum_{j \neq i} z_j u_{ij} + (z_i - 1)u_{ii}] = \frac{1}{M-1} [\sum_{j=1}^n z_j u_{ij} - u_{ii}],$$

given the state  $z = \{(z_1, \dots, z_n) \mid z_i \in \{0, 1, \dots, M\}, \sum_{i=1}^n z_i = M\}$ .

Rational agents select the technology which gives them the highest expected payoff. However, some agents make erroneous decisions. They choose the technology that may not give them the highest expected payoff. Two factors determine the probability of mutation interactively. Let the error rate be  $\varepsilon \in (0, 1)$ . Suppose potential mutants have a prior belief about the popularity of technologies. Denote this belief as the distribution,  $m = (m_1, \dots, m_n)$ , where  $\sum_{j=1}^n m_j = 1$ , and  $m_j \in (0, 1)$ . Agents choose technology  $j$ , with probability of  $m_j \varepsilon > 0$ , even though technology  $k$  provides them the highest expected payoff.

Sizeable contribution notwithstanding, this approach is not adequate in its treatment of incomplete information. Notice state  $z$  in the expected payoff function. Most of the agents in the model have complete information about the number of past adopters. The model attempts to incorporate incomplete information of agents

using the idea of mutation. It is more natural that agents do not have enough information regarding the number of past adopters. Hence, decision-making concerning technology adoption should be modeled jointly with information acquisition (Wozniak, 1993).

Young (1993, 1998) introduces sampling to a game similar to Arthur (1989). Assuming none of the agents have enough knowledge of technology popularity, an agent collects data on past technology adoption by other agents in opponent groups. Sample range is limited over the agent’s bounded memory of the last  $m$  periods. Agents calculate expected payoffs based on the sample and choose a technology in order to maximize their expected payoffs. Some agents select a technology randomly with an error rate of  $\varepsilon$ , regardless of their expected payoffs. These agents are analogous to mutants in Kandori and Rob. Despite the similarity, Young’s model includes two channels where errors can arise: mutation and sampling bias. The approach is a more pertinent treatment of incomplete information.

Let us illustrate Young’s model using a simple case. Suppose there are two disjoint groups of agents in population, R and C, with heterogeneous tastes. Each agent chooses a technology, A or B, with the following payoff matrix.

		Column	
		A	B
Row	A	a11, b11	a12, b12
	B	a21, b21	a22, b22

Agents’ utility varies depending on a technology’s popularity. Let  $p_{it}$  be the proportion of  $i$  agents who have chosen technology A up through time  $t$ , and  $1 - p_{it}$  be the proportions who have chosen technology B, where  $i = r$  for row agents and  $c$  for column agents. Each agent draws a random sample of size  $s$  from the past decisions of the other agent over his/her bounded memory of the last  $m$  periods. Agents judge the probability vector  $(p_{it}, 1 - p_{it})$  based on his/her sample. Table 1.3 shows the expected payoff for each agent at time  $t$ . Agents choose a technology consistent with utility maximization. However, there is a minor probability,  $\varepsilon$ , that agents choose a technology randomly. We call this probability an error rate. The error rate incorporates erroneous decisions due to incomplete information about market prosperity. In addition to incomplete information causing error, some entrepreneurs, who have the long-run prospect, may want to try either technology regardless of their myopic expected payoffs. Young proves that, if agents have only incomplete information (more precisely,  $0 < s/m < 1/2$ ), the technology adoption process converges to an efficient equilibrium independent of history (i.e., ergodic).

Previous results can be reproduced more generally under Young’s framework. Agents in Arthur’s model know the exact number of past adopters of technologies. Notice that, if the sample size  $s$  increases, then the empirical frequency distribution  $p_{it}$  approaches to the true probability in the entire population,  $p_{it}$ . Arthur’s model is the extreme case where the sample size corresponds to infinite memory, and no error.<sup>3</sup> In fact, Kaniovski and Young (1995) show that, with a sufficiently large sample size and a sufficiently small error rate, the stochastic process of technology adoption results in either technology being adapted (if there exist two pure and one mixed equilibria). The result of equilibrium selection is unpredictable since it depends on the initial state of the process. Thus, the problem of path-inefficiency remains (i.e., an efficient equilibrium is not guaranteed).

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<sup>3</sup> His approach is classified as a fictitious play with infinite memory. A fictitious play means that agents “choose best replies to the empirical distribution of their opponents’ previous actions [Young (1998), p. 28].”

The analyses in Kandori and Rob (1995, 1998) and in Young (1998) imply that government intervention is unnecessary. The market selects a Pareto efficient equilibrium in their models, without government intervention. The literature also provides a negative opinion regarding policy adjustments. However, their rationalizations are different from that of Kandori and Rob and Young (Cowan, 1991; Dalle, 1997). Dalle (1997) argues that government intervention is valid only when governments have an informational advantage over adapters regarding the quality of technologies. This is analogous to policy implications derived from the rational expectation hypothesis in Macroeconomics. There is no reason to believe that governments are better informed than agents in the market. Additionally, the effects of mutation are trivial when compared to influence of network externalities (or global externalities). The standardization of dynamically inefficient technologies is likely to occur. Market failures caused by network externalities are beyond governments' control.

**Market Share And Agents' Tastes**

Similarly, Kandori, Mailath, and Rob (1993) can be remodeled using Young's framework. Kandori, Mailath, and Rob provide a proto-type of Kandori and Rob. The former considers the selection of two technologies. We use a symmetric payoff matrix since their analysis assumes a single population (or homogeneous taste among agents).

	<b>Column</b>	
	A	B
Row	A	0, 0
	B	a22, a22

Let  $p_t$  be the proportion holding technology A in the population of size  $m$  at time  $t$ . One agent is drawn from the population at random. The agent draws a random sample of size  $s$  from the population. The agent evaluates their expected payoff based on the sample proportions,  $p_{t'}$ . An agent has an expected payoff of  $a_{11}p_{t'}$  with the selection of technology A, and has an expected payoff of  $b_{22}(1 - p_{t'})$  with the selection of technology B (see Table 1.4). With probability  $1 - \epsilon$ , the agent chooses either technology A or B, maximizing the expected payoff. With probability,  $\epsilon$ , the agent plays a random strategy with an equal chance of selecting either technology.

Kandori, Mailath, and Rob's model does not differ substantially from Young's model regarding Pareto efficiency of equilibrium. The two models do differ in agents' preferences, homogenous tastes (symmetric payoffs) in Kandori, Mailath, and Rob's model, and heterogeneous tastes (asymmetric payoffs) in Young's model. Heterogeneous tastes play a role in determining a market share (i.e., whether the market will be divided among technologies or not), but are irrelevant regarding the selection of an efficient technology. Young's general analysis incorporates Kandori and Rob's model. Kandori and Rob's implications are still valid under Young's framework. The market selects socially desirable outcomes with bounded, rational agents.

Previous works with unbounded (or infinite) memory yield the same implication. Arthur, Ernoiev, and Kaniovski (1987) show that technology adoption converges to either one of the  $r$  technologies or to a split market share. A split market occurs if the effects of heterogeneous tastes dominate network effects. In Arthur's example, a split market results with a nonlinear payoff, such as  $a_r(1 - \exp(-rn_a))$  for  $R$  agents. Similarly, Kaniovski and Young (1995) prove that, if there is only a unique mixed equilibrium, a technology adoption process converges, with probability one, to the equilibrium with sufficiently large sample size and sufficiently small error rate.

## **STRATEGIC PRICING AND LOCAL EXTERNALITIES**

This section discusses possible restrictions in the Kandori and Rob and the Young models. A good place to start is with the competition between Beta and VHS videocassette recorders. Beta (developed by Sony) lost its market share to the latecomer, VHS, and withdrew from the VCR market, despite its better visual quality. It is known that VHS could catch up with Beta, and eventually dominate the VCR market, partly because its license was shared among rivalry manufactures. Inter-firm coordination reduced the price of VHS via collaborative R&D efforts among manufactures. Hence, it is *not* always true that a superior technology will survive in the market by driving out an inferior technology.

Pricing strategies by companies (or sponsors) perform a crucial role in deciding market share. The models in the previous section focus on the demand side and miss the interaction between supply and demand. Katz and Shapiro (1986) highlight the importance of strategic pricing. They consider a two-period model where agents select either a sponsored or unsponsored technology. Their analysis shows that the sponsored technology is more likely to be adopted. A sponsored technology establishes market dominance by pricing below marginal cost in the first period. Such investment is compensated by pricing above marginal cost in the second period. Amable (1992), in a more recent work, makes a similar point.

Contrary to these works, the stochastic evolutionary models may be perceived as a discussion focused on unsponsored technologies. In the VCR example, license sharing and collaboration provide cost advantages to VHS producers. The seminal work of Katz and Shapiro and their successor provide a good explanation of the standardization of technology using pricing strategies.

Objections to the discussion above have been raised. The aforementioned non-evolutionary game literature utilizes agents with perfect foresight (e.g., Katz and Shapiro, 1986). The analysis is analogous to Arthur's model. A pricing strategy manipulates the level of absorbing barriers and promotes the lock-in of a sponsored technology. Arthur illustrates this using taxes and subsidies. The situation is a special case in evolutionary game models. Models by Kandori and Rob and Young handle cases that are more general by introducing mutation and bounded memory.

One may also claim that the evolutionary game approach implicitly includes the supply side arguments in agents' payoff functions. The payoff functions are increasing in the number of past adopters of a technology. This captures the convenience of sharing the same technology with other people. The embedded idea is that a popular technology increases the demand for the technology through a decreased price. A popular technology brings a higher level of current (and expected future) profits. This encourages investment in the technology. More investment improves the probability of successful R&D. Innovation reduces the price of the technology via lower production costs. This logic (discussed by Amable, (1992)) is implicitly captured by the fact that expected payoff functions are increasing in the number of past adopters.

Next, Kandori and Rob and Young models perceive network externalities as global externalities, but not as local externalities. Agents in their models are concerned with the number of past adopters of technologies in the population. Individual's decision-making regarding technology adaptation is likely influenced by the community rather than by the population. For example, take a case where an individual is about to buy a DVD recorder. Yet the individual is unfamiliar with the popularity of products. That person will probably ask their community, their friends and colleagues about their DVD recorders.

Simulation studies yield different conclusions, which depend on a variety of scenarios. An and Kiefer (1995) show standardization of a superior technology assuming sponsored technologies, revocable decision, and local externalities. Dalle (1997) considers the trade-off effect between diversity and coordination. Agents have heterogeneous tastes. However, they can benefit from the selection of a popular technology in the community due to local externalities. He reveals that technologies can coexist when heterogeneous tastes effects dominate the effect of local externalities. One technology survives with niches when the effect of local externalities dominates heterogeneous taste effects. A pure standardization of technology appears when global externalities are included along with local externalities and heterogeneity.

The literature in area of non-evolutionary game theory is also informative (Karshenas and Stoneman, 1993; Stoneman and Kwon, 1996). In these models, five factors determine technology adoption under network externalities. They are characteristics of agents, the number of past adopters, the timing of adoption, the cost of adoption, and information asymmetries among agents. Their analysis considers the situation where an uninformed agent acquires the information about technologies from informed agents. The decision of uninformed agents is affected by those with whom they have contact (i.e., local externalities). Costs of adopting a technology vary, since each agent has different abilities regarding learning the nature of technologies. Using a case study from the U.K. engineering industry, empirical analysis indicates the difficulty in determining which factors play a dominant role in technology diffusion. The reality is so complicated.

It is difficult for a government make inferences regarding an industrial policy's effectiveness when outcomes vary on a case-by-case basis. Kandori and Rob (1998) provide a clear-cut role for the government: governments do not have to take any action. The market mechanism selects the superior technology. Their new analysis incorporates characteristics of technologies such as prices, quality, and compatibility as costs of technology adoption. Specifically, they distinguish inward incompatibility (i.e., the degree of compatibility that a technology can use other technologies) from outward incompatibility (i.e., the degree of compatibility that other technologies can use the technology). Even with the relaxed assumptions, their results from the previous model are still valid. A Pareto dominant technology is attainable as a unique long-run equilibrium, independent of the initial state.

Finally, the stochastic evolutionary game models lose their predictive power if either technology is not Pareto dominant over the other technology. Consider, for example, the case of driving on the right-hand-side or left-hand-side of the road. We keep right in the U.S. when driving a car, but Japanese keep to the left. Correspondingly, driver's seats are on the left side of U.S. cars and on the right side of Japanese cars. Each country chooses a different rule, though most Americans and most Japanese are right handed. Another example appears in Kirman (1993). This study examines the choice between two identical, adjoining restaurants. When either technology is not superior to each other, either one or the other becomes dominant in the market. Fortunately, in this case, it is not of great consequence which technology is adopted, since both technologies are efficient. Government intervention is not an issue in this case.

## **CONCLUDING REMARKS**

This paper considers a dynamic technology adoption process in the presence of network externalities. It does so by referring to findings in stochastic evolutionary game theory. The results of equilibrium selections have important implications for the role of governments. While the seminal work of Arthur (1989) illustrates the possible path inefficiency, Kandori and Rob and Young models show that the market attains a Pareto efficient outcome even with the presence of network externalities. The new concepts of mutation and bounded memory make the results of Kandori and Rob and Young appealing. Neither analysis prescribes the necessity of government intervention.

While the analyses are verisimilar, we should be careful interpreting their policy implications. The analyses do not answer questions pertaining to convergence in the technology adoption process. It may take long time for the market to reach equilibrium. This point reminds us of macroeconomic policy arguments between New Classical and Keynesian economists. New classicalists avoid government intervention. Market mechanisms attain equilibrium in the long- run. Keynesians claim that the process is too slow. Government intervention is required to resolve disequilibrium (such as an unemployment) in the short-run. Long waiting time until equilibrium introduces other elements important to consider. An example involves changes in the number of technologies, as in Ellison (1993). Although several literatures assume a constant number of technologies in the market, withdrawals from and entries into the market of technologies occurs frequently. As a result, the quality of technologies also evolves over time.

Another interesting extension involves considering the diffusion process of a local standard into a global standard. An issue of recent political interest is the standardization of accounting systems worldwide. Accounting systems are developed in each country, in the presence of local externalities. The global economy requests integration of each local system into a global standard. The analysis here provides governments with potentially useful



information concerning this issue. Similar types of policy implications will be relevant when planning global standards (such as taxation) for international business.

We may want to extend the argument to include plural technology adoption. Acquiring language skills is an example. Descendants of foreign-originated citizens are often bilingual (i.e., their parent's tongue and English). In some cases, agents may adopt a few, new, technologies without abandoning a current, old, technology. Additionally, language adoption provides a framework for examining the interaction between local and global externalities. Agents learn languages from communities, their families and school friends. They are also influenced by society as a whole, via media influences. Technology adoption can be formalized as a function of agents' abilities, along with cultural characteristics. Some foreign-originated citizens are observed to make a greater effort to maintain their original cultures when compared to others. Social policy implications could be inferred from this type of analysis. The aforementioned topics represent potential future lines of research.

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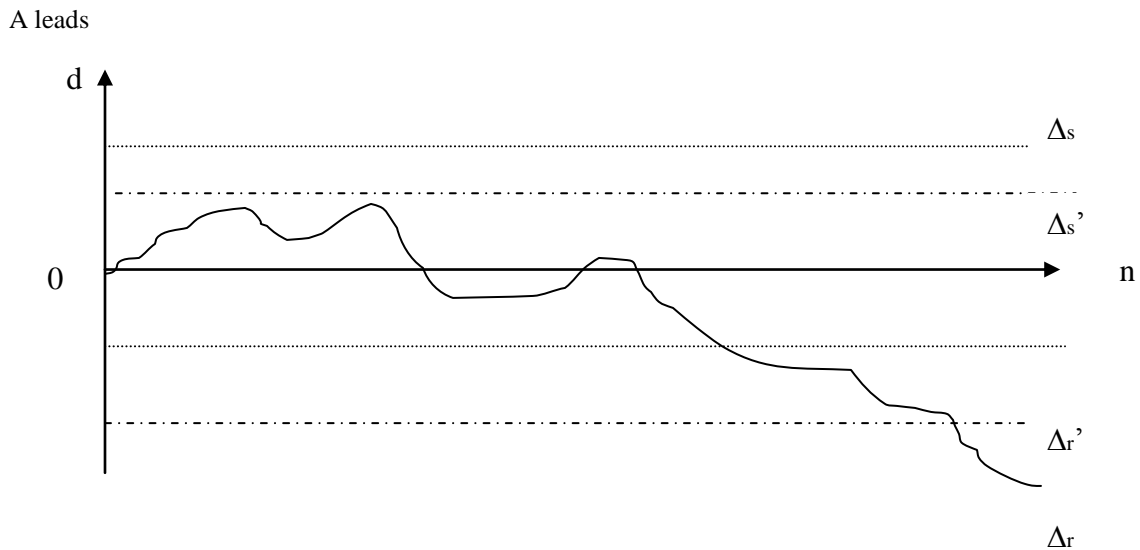
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**Figure 1 - Stochastic Process Of Technology Adoption**



**Table 1 - Payoff Matrixes**

**Table 1.1**

	<b>Technology A</b>	<b>Technology B</b>
<b>R-agent</b>	$a_r + rn_a$	$b_r + rn_b$
<b>S-agent</b>	$a_s + sn_a$	$b_s + sn_b$

**Table 1.2**

	<b>Technology A</b>	<b>Technology B</b>
<b>R-agent</b>	$a_r + rn_a + g$	$b_r + rn_b - t$
<b>S-agent</b>	$a_s + sn_a + g$	$b_s + sn_b - t$

**Table 1.3**

	<b>Technology A</b>	<b>Technology B</b>
<b>R-agent</b>	$a_{11}pct^2 + a_{12}(1-pct')$	$a_{21}pct^2 + a_{22}(1-pct')$
<b>C-agent</b>	$b_{11}prt^2 + b_{21}(1-prt')$	$b_{12}prt^2 + b_{22}(1-prt')$

**Table 1.4**

	<b>Technology A</b>	<b>Technology B</b>
<b>agent</b>	$a_{11}pt'$	$b_{22}(1-pt')$

NOTES