A Cellular Automata Model of Competition in Technology Markets with Network Externalities

Judy Frels[*], Debra Heisler[+], James Reggia[+], and Hans-Joachim Schuetze[*]

[*] Robert H. Smith School of Business and [+] Dept. of Computer Science,
University of Maryland, College Park, MD 20742 USA

Abstract. In network markets, the utility a consumer gains from a product increases with the number of other consumers adopting that product. We examine the evolution of such markets using stochastic cellular automata (CA) models to simulate consumer adoption and pricing strategy decisions. Two firms, which lie outside of and interact with the CA model, sponsor incompatible technologies and compete for market dominance using various penetration pricing strategies. We study markets where the two technologies are equal in capability and where they have asymmetric capabilities. We find that the importance of the network to the consumer is critical in determining the financial success of enacting pricing strategies: penetration pricing in a market where network externalities are only moderately important to the consumer can be disastrous. We also find that while an inferior technology may gain substantial market share by price-cutting, it is not likely to gain financial rewards. Finally, we find that if a penetration pricing strategy is to be enacted, more aggressive strategies with larger price cuts lead to greater success.

1 Technology Markets with Network Externalities

Expanding the scientific understanding of collective human behavior and decision making is of interest in many fields, including psychology, sociology, economics, and business management. Cellular automata (CA) models provide a potentially powerful framework for investigating the collective behavior of people, in part due to their explicit representation of space, and their focus on concurrent local computations that lead to self-organization and "emergent behaviors". Limited past work has used CAs to examine such issues as spatial segregation of human populations [1], sales patterns in marketing [2], dissemination of culture [3], evolution of cooperative behavior [4, 5], traffic flow [6], and urban growth patterns [7]. Closely related multi-agent models using simple local interactions in cellular grids have examined issues such as the distribution of wealth [8] and the emergence of communication [9, 10].

In this paper we describe our research using a CA model to investigate human decision making during the adoption of new technology. In many markets, particularly information technology markets, consumers gain benefits from doing what other consumers do, i.e., from adopting compatible products. Such markets are called *network markets* [11, 12] because the value that a consumer gets from a product depends on the network of other consumers associated with that product. For example, tele-

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phones and fax machines are valuable only when other people (a "network") have purchased such products. Network markets tend to be "tippy" or "winner-take-all," meaning that as one product gets ahead, it becomes more attractive to the next adopter who, upon adopting it, makes it even more attractive to the next adopter (e.g., VHS vs. Betamax video recorders). Thus, one characteristic of such markets is that often only one technical standard is likely to prevail, and because the value the network provides can overwhelm the value provided by the technology itself, it is possible that the prevailing standard will not be the most technologically advanced.

In such markets, management may adopt strategies to ensure the market tips in their direction rather than their competitor's. Strategies appropriate in network markets often run counter to recommended strategies in non-network markets because it can be critical for a firm to gain an early lead in adoption [11]. Thus, in such a market, it may be worthwhile to pursue strategies that are not immediately revenue enhancing under the assumption that greater revenue can be captured once the market has tipped in the firm's direction. Examples of strategies suggested to managers of network markets include penetration pricing, signaling, product improvements, preannouncements, licensing of the technology, and support for development of complementary products [11, 13]. In this research, we examine the efficacy of a selection of penetration pricing strategies.

2 Methods

We study a CA model of human decision-making in network markets. Our primary goal is to better understand the effects of different pricing strategies that a business can take to promote adoption of its technology where decisions by one consumer affect those of others. Another goal is to assess the effectiveness of CA models as an investigative method for answering real-world questions involving complex socioeconomic systems. Our research is conducted in an artificial world we call *Standard-Scape*, where active cells are viewed as *agents* representing adopters (individual consumers or firms) who choose between two incompatible technological products (A or B) and whose goal is to maximize their utility. We also model technology sponsors representing firms competing to achieve a dominant market share and then recoup their investment in this CA-simulated market. The technology sponsors are external to but interact with and influence the CA model. Each technology sponsor firm has a cost of goods sold, and we track the revenue each firm obtains from the agents adopting its products. If, through the various strategies enacted, the technology sponsors deplete their capital, they go out of business. Their strategy is based on penetration pricing, as follows. When a firm has a market share it does not deem sustainable, it lowers its price to gain further market share. When a firm has a market share that it deems "dominant" and overall market penetration by all providers is significant, it raises its price to recoup earlier revenue foregone by price cutting and to take advantage of its near monopolistic situation [14].

The current set of simulations was done in a 60x60 cellular space having 600 randomly located cells designated to be agents/consumers (see Fig. 1). Agent cells have *multi-attribute states*, i.e., states composed of multiple fields [15]. For example, one field is *Product-Adopted* and can take on values *N* (neither product), *A* (product A adopted) or *B* (B adopted). All non-agent cells are permanently quiescent. Each agent/consumer cell updates its state based on the state of just those agents (about 18 on average) in its local 11x11 neighborhood. In each time period (conceptualized as a month in this setting), agents seek to adopt a product (A or B) that maximizes their utility. Adopting a product creates network externalities (as well as switching costs) that then influence agents' future decisions. We model a multi-period adoption scenario because repeated adoption is common in business settings [12]; agents may revert from A or B to neither.

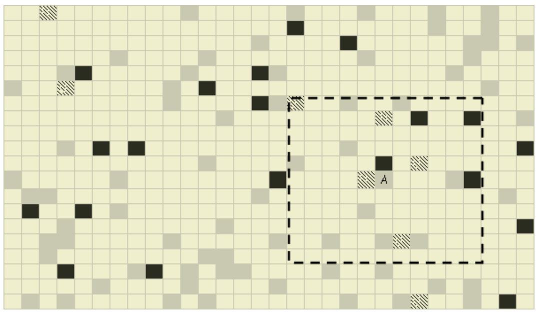

Fig. 1. A portion of the CA space, where quiescent cells are white, and agents adopting product A, B, or neither are shaded cells. The agent labeled "A" here can only observe the state of other agents within its neighborhood (dashed lines)

Cell state changes are determined by a consumer/agent's utility function that is based on a multi-attribute model [16] reflecting the stand-alone technological value of the product, the price of the product, the network of users associated with the product, the consumer's expectations of the future size of the network [11], and the agents' switching costs [17]. In the equation below, *p* designates a particular product, *i* designates an individual consumer agent, and weights $w1_i$—$w5_i$ are positive and sum to 100. Agent *i*'s utility U_{pi} is:

$$U_{pi} = w1_i(Tech_p) - w2_i(Price_p) + w3_i(Network_{pi}) + w4_i(Expect_{pi}) + w5_i(Investment_{pi})$$

where $Tech_p$ represents the performance rating of each of the technologies A and B, $Price_p$ represents the price of each technology (initially \$100 for each), $Network_{pi}$ is calculated as ln(number of neighbors who have bought product p) / ln(total number of neighbors), $Expect_{pi}$ represents agent-specific expectations about the future size of the user network for products A and B [11], and $Investment_{pi}$ represents the investments an agent has made in product A or B to date or their switching costs.

At each time tick, each simulated consumer agent attempts to purchase the technology with the greatest utility provided that the consumer agent has sufficient capital, and that the utility of the chosen product is greater than the reservation utility of *Threshold* (the amount of utility above and beyond the price that a product must provide in order for the consumer to purchase a product rather than choosing "no choice" as a preferred option). Each time period consumer agents are endowed with an increment of capital ($100) that they are able to spend on technology A or B or save for future spending, depending on their utility function. If they purchase a product, an amount of capital equal to the price of the product (set by the technology sponsor agents) is transferred to the technology sponsor agent as payment. The technology sponsor agents amass capital by a simple calculation of revenue (payments) minus the cost of goods sold ($25 for each item). Summarizing, the state of each agent cell *i* consists of the values of Product-Adopted$_i$, Expect$_{Ai}$, Expect$_{Bi}$, Investment$_{Ai}$, Investment$_{Bi}$, and Capital$_i$, all of which vary during a simulation. Each agent also has *fixed* weights $w1_i$ – $w5_i$ indicating the relative importance of the factors in its utility function. To provide reasonable estimates for these weight values, we collected data from 141 subjects on cell phone feature adoptions that allowed us to estimate their subjective weights using conjoint analysis (space limitations prevent describing this study here). The weights and thresholds used for each of the 600 agent cells in our simulations were randomly sampled, with replacement, from these 141 actual consumers.

Our model is stochastic for several reasons. First, agents are randomly placed. Second, when the product that maximizes the consumer's utility is determined, that product is adopted only with 85% probability to account for events outside the model [18]. Third, expectations regarding the future size of the product networks ($Expect_{pi}$) are randomly assigned to each agent. These values are updated through the duration of the run to reflect the market's evolution. Upon creation, each agent is set to change its expectation every 1 to 12 time ticks. This number is randomly generated and fixed for that agent throughout the run. When it is time for an agent to change its expectation, it will update it based on which technology the majority of its neighbors bought during the last time tick. The expectations are modified by a random number between 0 and 1. The expectation for the technology with the larger market share goes up by the fraction, while the expectation for its competitor goes down by the fraction. The expectations have a minimum of 0 and a maximum of 100.

The two technology sponsors/firms for products A and B are able to take action simultaneously every three time periods (i.e., once per quarter) and react to the market penetration they observe. Each technology sponsor agent has two internal variables: *MktShareTrigger* which describes the market share this sponsor agent wants to achieve once at least 80% of the market has been penetrated; and *PricingFactor* which describes the percentage by which the sponsor will raise or lower the price of the technology. Firms can observe the market share they and their competitors have achieved, as well as overall market penetration. When the market penetration is less than 80%, considered low market penetration, the technology sponsor will lower its price by the PricingFactor in order to attract more buyers. If the market penetration is high (over 80%) the technology sponsor will do one of three things based on its current market share and its MktShareTrigger. When the sponsor's market share is between 20% and its desired market share (MktShareTrigger), the technology sponsor will lower its price by the PricingFactor. When the sponsor's market share is above its desired market share, the technology sponsor will raise its price by the PricingFactor to recoup its earlier investment in obtaining this market share. When the sponsor's market share falls below 20%, the technology sponsor will do nothing in order to retain its loyal customers. Sponsor agents accumulate capital as long as they sell at a price above their costs. Sponsor agents may sell below their cost, but can only operate for 36 time periods (i.e., 36 months, three years, or 12 quarters) with negative capital. After 36 time periods with negative capital, technology sponsor agents will exit the market (i.e., go out of business.)

Simulations were run in a 5 (pricing strategies) x 2 (importance of network) experimental design. We developed a menu of pricing strategies (MktShareTrigger and PricingFactor) to be enacted by the inferior technology. In all cases except the most basic runs (described below), the inferior technology enacts one of the strategies and the superior technology enacts the least aggressive strategy. We then examine the effectiveness of these strategies in market share and income gained. Market share triggers for price cuts were either 20% or 65%, and penetration pricing factors either 20% or 50%. In the "Most Aggressive" strategy, the technology sponsor will cut price by 50% when its market share drops below 65%. In the "Least Aggressive" strategy, the technology sponsor agent cuts price by 20% when its market share drops below 20%. In the "Itchy but Weak Trigger Finger" (IWTF) strategy, the technology sponsor is quick to cut prices (below 65% market share) but does so by a modest amount (20%). In the "Desperation" strategy, the technology sponsor waits to cut prices until the market share has dropped below 20%, but at that point, cuts them significantly (50%). Each simulation reported below was run 30 times for each experimental condition, so each table entry in the Results that follow is the mean over those 30 runs.

3 Results

The first two rows of Table 1 summarize the results after 5 years when two equal technologies ($Tech_A = Tech_B = 70$) compete in an environment where network externalities are important. Differences in left-to-right-adjacent table entries are statistically significant ($p < .05$) unless marked with an asterisk. As seen here, a more aggressive penetration pricing strategy by technology A leads to larger numbers of adopters and also to greater income. Even when met with meager price-cutting by the competition, this most-aggressive penetration pricing strategy proves successful both financially and from a market share standpoint. This can be contrasted with the outcomes when the network is less important in the consumer agents' utility function (Table 1, last two rows). In these cases, the aggressive network development strategy is somewhat successful from an adoption standpoint, but is always disastrous from a financial standpoint. Further, when the most aggressive strategy is countered by even the smaller price cutting strategy on the competitor's part, both firms lose money. Thus, while A's aggressive pricing strategy consistently gave it a larger market share, it only profited financially when network externalities were important.

Table 1. Equal Technologies, Firm A Implements Most Aggressive Strategy (N=30)

B's Strategy	Network Importance	A's Income	B's Income	Agents Adopting A	Agents Adopting B
No Action	High	176,690	87,245	477.2	9.6
Least Agr.	High	171,085	61,056	422.9	61.5
No Action	Low	-21,307	121,205	444.7	20.1
Least Aggr	Low	-16,880*	-40,261*	290.5	170.6

What if, instead of two equal technologies, one is technically inferior to the other? Table 2 shows the results after 5 years when the firm with the inferior technology (*Tech* = 56) pursues different pricing strategies while the superior technology firm (*Tech* = 70) follows a least-aggressive strategy. The superior technology usually gained a larger market share in all situations except when the inferior technology firm used a most aggressive pricing strategy in a high-importance network market; even then the inferior technology only obtained a marginal market share victory at the expense of a net negative income. The same pattern of results was found when simulations were allowed to continue for over 16 years (data not shown). Thus, our results provide no clear support for believing that inferior technologies can use penetration-pricing strategies effectively to capture the largest market share when agents see only their local neighborhood.

Table 2. Unequal Technologies, Superior Tech. Firm Uses Least Aggressive Strategy

Inf. Tech. Strategy	Network Importance	Inf. Tech. Income	Sup. Tech. Income	Agents Adopting Inf. Tech.	Agents Adopting Sup. Tech.
Base	High	210,290	904,935	47.4	216.6
Least Aggr.	High	18,021	207,037	74.1	405.0
Desperation	High	24,227	166,148	194.3	289.1
IWTF	High	-3,389	254,383	92.4	391.1
Most Aggr.	High	-3,040	180,200	272.7*	207.6*
Base	Low	207,500	518,640	45.8	121.0
Least Aggr.	Low	-8,402	-69,052	89.3	375.5
Desperation	Low	12,748	-85,833	68.4	384.7
IWTF	Low	-6,116	-79,691	77.5	389.3
Most Aggr.	Low	15,566	-81,373	36.8	416.0

Table 2 also indicates that whenever the inferior technology firm undertakes any penetration pricing strategy and the network importance is low, the inferior technology will, on average, receive as much or more income than the superior technology. In contrast, when the network is more important, the superior technology always dominates the inferior in terms of income achieved. The same pattern of results is found when we allow the simulations to run for more than 16 years. Thus, the importance of network externalities to consumers in a market had a major impact on income received.

Finally, we compared the success of strategies enacted by the inferior technology against a superior technology that consistently applied the least aggressive strategy. We found in these and other simulations (data not shown) that both technology sponsors are most financially successful when the inferior technology pursues no penetration pricing at all. On average, the superior technology (enacting a least aggressive strategy) achieves greater income in the base case of no penetration pricing by the inferior technology (mean $711,788) than with any pricing strategy as does the inferior (mean $208,895). Further, the superior technology sees significantly fewer agents adopting in the base scenario compared to all other strategies, an average of 168.8.

The inferior technology see the fewest adopters under the base strategy with an average of 46.6, but this is not significantly lower than in the IWTF (mean 85.0) or Least Aggressive strategies (81.7). The inferior technology obtains the greatest number of agents adopting by using the Most Aggressive strategy (154.8) or Desperation strategy (131.4). The superior technology gains the most agents when the inferior technology employs the Least Aggressive (mean 390.3) or IWTF (mean 390.2) strategy. By the end of year 5, the superior technology sponsor never goes out of business. The inferior technology sponsor agent does go out of business twice when using the Desperation strategy and three times when using the Most Aggressive strategy, both when the network is less important. When we allow simulations to continue for over 16 years, we see much greater frequency of sponsors going out of business. The Least Aggressive and the IWTF (Itchy but Weak Trigger Finger) strategies were most prone to putting the inferior technology sponsor out of business. Both of these strategies involve price cuts of only 20%. In contrast, the superior technology appears to be most likely to go out of business when the inferior technology sponsor adopts the Desperation or Most Aggressive penetration pricing strategy. Both of these strategies involve price cuts of 50%

4 Discussion

Our simulations produced a number of interesting results from a business management perspective. First, the importance of the network to consumers was found to be crucial in determining the success of penetration pricing strategies. A dramatic difference in results occurred when the network was more heavily weighted in the consumer's utility function versus when it was not. Thus, misinterpreting the relevance of network externalities to a firm's potential market, although it may lead to successful market share development, may also lead to disastrous financial results. Also, when technologies are symmetric and when a firm has "lost" the market share battle, little was to be gained by even mild price-cutting. Second, when technologies are asymmetric, an inferior technology sponsor enacting a penetration pricing strategy may occasionally achieve market share success but that success is not necessarily tied to financial success. Finally, we observed that no penetration pricing at all brings the greatest financial reward to the sponsor agents, although it achieves very low market penetration. It is possible that this just reflects the manner in which we implemented the pricing rule; it is probably more reasonable to compare outcomes of different strategies to one another given that they are all implemented with the same biases. Within the strategies, we found that strategies with larger price reductions led to the largest number of adopters for the inferior technology. These same strategies, enacted by the inferior technology sponsor, are also most damaging to the superior technology's financial and market share position. Despite the market share results achieved with the Desperation and Most Aggressive strategies, such price cuts did not necessarily lead to better or worse financial success for the inferior technology. However, in terms of punishing a competitor with a superior technology our results suggest the value of true penetration pricing rather than modest price cuts in a network market.

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