

The Chilling Effects of Network Externalities

Jacob Goldenberg
School of Business Administration
Hebrew University
Jerusalem, Israel 91905
msgolden@mscc.huji.ac.il

Barak Libai
Leon Recanati Graduate School of Business Administration
Tel Aviv University
Tel Aviv, Israel 69978
libai@post.tau.ac.il

Eitan Muller
Leonard Stern School of Business
New York University
New York, NY 10012
Leon Recanati Graduate School of Business Administration
Tel Aviv University
Tel Aviv, Israel 69978
emuller@stern.nyu.edu

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Abstract

Conventional wisdom suggests that network effects should drive faster market growth due to the bandwagon effect. However, as we show, network externalities may also create an initial slowdown effect on growth because potential customers wait for early adopters, who provide them with more utility, before they adopt. In this study, we explore the financial implications of network externalities by taking the entire network process into account. Using an agent-based as well as an aggregate-level model, and separating network effects from word of mouth, we find that network externalities have a substantial chilling effect on the net present value associated with new products. This effect may occur not only in a competitive framework, such as a competing standards scenario, but also in the absence of competition. Drawing on the collective action literature in order to relate network effects to individual consumer threshold levels, we find that the chilling effect is stronger with a small variability in the threshold distribution, and is especially affected by the process early on in the product life cycle. We also find a “hockey stick” growth pattern by empirically examining the growth of fax machines, CB radios, CD players, DVD players, and cellular services.

Keywords: agent-based models; contagion; net present value; network externalities; new product growth; threshold levels

1. Introduction

How do network externalities affect the diffusion rate and the consequent economic value associated with a new product? Despite the sizeable academic literature on the dynamics of network goods markets, the answer to this question is not obvious. Network effects and network externalities exist when consumers derive utility from a product based on the number of other users; conventional wisdom suggests that such effects should drive faster market growth due to the bandwagon effect (Rohlfs, 2001; Shapiro & Varian, 1999; Economides & Himmelberg, 1995). Therefore, the rapid diffusion of fast-growing product categories has been attributed to network externalities (Doganoglu & Grzybowski, 2007).

However, initial network effects may also have a chilling effect on growth due to the “wait-and-see” position adopted by consumers who derive little utility from an innovation that has few other adopters (Farrell & Saloner, 1986). Therefore, the growth of network goods may follow a two-stage process, that is, slow initial diffusion followed by a very fast growth stage (Rogers, 2003). The question remains as to the overall network effects with respect to the time it takes an innovation to develop. This growth rate is of considerable managerial importance due to the time value of money, as acceleration in growth can translate into a sizeable difference in the Net Present Value (NPV) of an innovation. However, little is known about the NPV impact of network externalities with respect to the growth rate and the factors that drive it. This lack of knowledge is noteworthy given the growing interest in optimal product strategies for network goods. Various market entry strategies or reactions to market entry of network goods have been suggested in recent years (Sun, Xie & Cao, 2004; Lee & O’Connor, 2003; Montaguti, Kuester & Robertson, 2002). Such strategies typically have an impact on or are affected by the rate of growth of the network good in question. A change in the economic value of network goods due to the growth rate should therefore be taken into account in any such analysis.

In this study, we analyze the fundamental effects of network externalities on new product growth rates and consequent profitability. To do so, we combine a classical diffusion model similar to the Bass model with a social threshold model consistent with the collective action literature in sociology (Chwe, 1999; Macy, 1991; Granovetter, 1978). We apply two modeling approaches toward this goal. First, we apply an agent-based model to simulate the growth of the market for a given network good. This bottom-up approach enables us to understand how individual-level network goods decisions aggregate to market phenomena. We compare the profitability of similar growth processes with and without network externalities and examine how market characteristics affect the difference. Second, we present an aggregate diffusion modeling approach that enables an analysis using market-level data that is analogous to our first estimation. Consistent with diffusion research, all analyses as well as profitability measures are conducted at the industry level. A brand-level analysis of this diffusion process, even without network externalities, is beyond the scope of this paper (Libai, Peres & Muller, 2009a, 2009b).

Our work is consistent with recent calls for a better understanding of how network externalities affect the takeoff, growth, and decline of products (Hauser, Tellis & Griffin, 2006). We find that network effects have an overall chilling effect on the profitability of new products. While the bandwagon effect can indeed lead to fast growth later on, the likely decrease in growth rate early on together with the effect of the discount rate create a general reduction in the NPV. This result is consistent across a wide range of parameter values. We also show that this phenomenon can be strongly affected by the mean and variance in threshold distribution. We find that the wider the variability in threshold distribution in the population is, the weaker is the effect of network externalities on growth. Overall, these results are critical for planning and profit calculation in network goods markets.

The rest of this article continues as follows. We first discuss the possible effect of network externalities on the growth rate and then show how a threshold model can be combined with a classic diffusion setting using an agent-based approach. We conduct an experiment comparing markets with and without network effect. Then we provide an aggregate-level analysis and empirically examine the growth of fax machines, CB radios, CD players, DVD players, and cellular services. We conclude with managerial implications.

2. Network Externalities and Growth Rates

Due to their significance to numerous industries including technology, entertainment, and communications, the dynamics of network markets have received considerable attention in the past two decades. See Birke (2008), Farrell & Klemperer (2006) and Shy (2001) for reviews of economics and Stremersch (2007) for marketing literature. This dynamic setting contrasts with earlier work in economics that emphasized the state of equilibrium in network markets rather than the dynamic path toward that state (Economides, 1996; Esser & Leruth, 1988; Laffont, Rey & Tirole, 1998; Rohlfs, 1974).

Past literature has not yet reached a decisive conclusion on the effect of network externalities on the growth rate. Conventional wisdom suggests that network effects drive faster market growth due to increasing returns associated with such processes (Arthur, 1994). Economides and Himmelberg (1995), for example, suggested that introducing network externalities into a dynamic model of market growth “increases that speed at which market demand grows. Rohlfs (2001, p. 56) argued that “growth in demand generates bandwagon effects, which lead to further increase in demand; and so forth. As a result, demand may grow extremely rapidly.” Shapiro and Varian (1999) first attributed network externalities to positive feedback and then suggested that “if a technology is on a roll...positive feedback translates into

rapid growth: Success feeds on itself.”

However, networks can also create the opposite effect of slowing growth in what is sometimes labeled “excess inertia” (Srinivasan, Lilien & Rangaswamy, 2004; Farrell & Saloner, 1986). Early in the product life cycle, most consumers see little utility in the product, as there are few adopters, and so they may take a “wait-and-see” approach until there are more adopters. Hence, diffusion early on may be very slow and occur among the few consumers that see enough utility in the product even without adoption on the part of other consumers. Overall, the process may be characterized by a combination of excess inertia and excess momentum, i.e., slow growth followed by a surge (Van den Bulte & Stremersch, 2006; Rogers, 2003).

This growth pattern can occur via various types of network externalities. In the case of *direct network effects*, such as fax, e-mail, or other communication products, the number of adopters drives utility directly because the higher the number of adopters is, the higher is the utility of the product. Regarding *indirect network effects*, such as hardware and software products, a possible increase in utility may occur through market mediation (e.g., the number of DVD rental outlets), which in turn is a function of the number of adopters. Consumers will wait for a hardware adoption until there is enough software. In the case of competing standards, early adopters take the risk of adopting the wrong standard, so many wait until the winning standard is clear, and more importantly, which standard or platform will no longer be supported.

The precise dynamics of the impact of network externalities on the growth rate can be determined by the source of the externalities under examination. Past literature has pointed to two types of effects in this regard, namely, *local* and *global*. Under *global externalities*, a consumer takes into account an entire social system when considering the impact of the number of adopters on utility, whereas under *local externalities*, a consumer considers adoption in

relation to her close social network. Both approaches have been considered in the network goods literature (Farrell & Klemperer, 2006), and in many cases, both exist to some extent. However, explicitly modeling their joint effect is not trivial (Tomochi, Murata & Kono1, 2005). This *reference group effect* probably changes among various kinds of externalities. Regarding indirect externalities, the effect is expected to be more global, i.e., the vendor's decision to add more software typically depends not on local social network adoption but rather on the overall number of adopters or expected adopters. Therefore, user utility is affected by the total number of other adopters.

Competing standards growth will probably also invoke a global effect, since the “verdict” on what eventually becomes the *de facto* standard depends on the total number of users, not just those in the local social system. Some exceptions are worthwhile to note, as some standards have become *locally* dominant for long periods, such as Apple with artists and designers and Sony's Betamax videocassette format with broadcasters. In addition, the recent network effects literature has moved beyond considering the total number of users as the only characterization of network effects (Binken & Stremersch, 2009; Tucker, 2008).

The situation may be more ambiguous with direct network effects. One could argue that if an individual communicates mostly with her close social network, then the local utility from the number of adopters will drive adoption. Evidence for such effects has been largely based on geographic patterns of adoption, for example, in the case of personal computers (Goolsbee & Klenow, 2002). Yet, even under direct network externalities, users are often also quite interested in the overall utility that they may derive from communicating with others who are not necessarily in their close network. Indeed, communications researchers have argued that for interactive innovations such as fax, videoconferencing, and e-mail, growth and takeoff are driven

by *perceptions* of global utility, which in turn are based on overall market ubiquity (Rogers, 2003; Mahler & Rogers, 1999). For some communication products, global utility is evident. For example, for Citizens Band (CB) radio much of the utility follows the ability to randomly communicate with other users on the road or at travel sites. The same goes for many user-generated media sites and file-sharing sites in which users enjoy the presence and contributions of others who are not necessarily part of their social system.

While the literature on the diffusion of innovations does not offer a straightforward approach to modeling the growth of a market for a network good (Peres, Mahajan & Muller, 2008; Chandrasekaran & Tellis, 2005), there have been efforts to incorporate network effects into hazard growth models as part of the analysis of optimal pricing under competition (Xie & Sirbu, 1995).

A major challenge toward this end regards the multiple effects of previous adopters on the growth rate. Previous users are expected to accelerate growth due to interpersonal effects, including word of mouth and imitation, which is typically used to reduce both risk and search costs. Yet previous adopters also supply value through the increase in the utility of the network good. The literature on the modeling of the diffusion of innovations, specifically the Bass model (1969) and its extensions, generally do not separate the two, and a single parameter for internal influence is used to capture both the impacts of interpersonal communications and network externalities (Van den Bulte & Stremersch, 2004).

To consider how to separate the two, we note that for the adoption of a network good to occur, a potential adopter has to overcome two barriers. She has to be convinced via the communication process that the product is not risky and provides value as is the case for any other product, and she must be assured that the number of other adopters is such that the network

product will indeed supply the value it has the potential to provide. To incorporate this effect into our approach, we turn to social threshold models.

Social threshold modeling is grounded in the collective action literature that focuses on the emergence of public opinion. An individual's threshold is defined as the proportion of a group needed for her to engage in a particular behavior. Since individuals have varying threshold levels, those with low thresholds engage in the behavior early, while those with high thresholds do so after most of the social system has engaged in the collective behavior (Valente, 1995). Threshold models of collective behavior examine cases in which individuals engage in a behavior based on the proportion of others in the group already engaged in the same behavior (Yin, 1998; Macy, 1991; Granovetter, 1978). The threshold distribution helps to explain how social groups move from individual-level behavior to collective action with respect to strikes, riots, attendance at meetings, and migration (Granovetter, 1978).

Markets of network goods are suitable candidates for analysis using a social threshold approach because an adopter's utility from a product is directly affected by the number of other adopters using the product. Indeed, it has been suggested that threshold modeling is decidedly appropriate for analyzing network effects in consumer demand (Granovetter & Soong, 1986), particularly when analyzing markets for network goods such as new telecommunication services (Allen, 1988). The appendix presents a formal model of how the increase in utility due to other adopters can be related to a threshold distribution in the population. While this model is not necessary for the following analysis, since we assume that there is a distribution of thresholds in the population and do not focus on the exact way thresholds evolve, it helps in understanding that an individual's threshold will depend not only on the utility from the presence of other adopters but also on other product features and price. If a product's price is low, for example, it is

reasonable to expect that the thresholds of those who follow network externalities will be lower. Similarly, if the utility from a non-externalities product attribute is high, the relative role of externalities might be lower.

3. An Agent-Based Model (ABM) of Network Good Growth

In order to examine how network effects drive market growth, we use an agent-based modeling technique that simulates aggregate consequences based on local interactions between individual members of a population. Agent-based models are used to map actual situations in a “would-be world” while keeping realistic relationships accurate at the individual level. They are increasingly used in the social sciences to model social processes such as diffusion, collective action, and group influence (Smith & Conrey, 2007; Macy & Willer, 2002) as well as economic activity in general (Tesfatsion, 2003). They are also increasingly used in the marketing literature, particularly with respect to new product growth (Delre, 2007; Goldenberg, 2007; Shaikh, Rangaswamy & Balakrishnan, 2006; Garcia, 2005; Libai, Peres & Muller, 2005). Cellular automata modeling is an agent-based modeling technique that has been extensively used across disciplines to model social-based phenomena. We present a brief description of this method. For more details, see Sarker (2000) and Goldenberg, Libai, and Muller (2004).

The cellular automata modeling environment consists of a finite number of virtual individuals in a given simulated social system, each of whom is able to receive information and make decisions during consecutive, discrete periods. The cellular automata framework can be understood as a matrix of cells in which each cell, representing a potential consumer, can take one of two states, namely, “0” representing a potential consumer who has not adopted the innovative product and “1” representing a consumer who has adopted the new product. The eight cells surrounding a given cell, which are marked in gray in Figure 1, represent the personal

“neighborhood” of the consumer. This personal neighborhood generates the potential communicators for this consumer.

Figure 1 - Cellular automata adoption

0	1	1	1	1	1	1	0	0	1
0	0*	0	1	1	1	1	1	1	1
0	0	0	1	1	1	1	1	1	1
0	1	1	1	0	1	1	1	0	1
0	1	1	0	0	1	1	1	1	1
1	1	0	0	1	0	1	1	1	1
1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1

Note that other personal networks could be envisioned, as the structure of personal networks in a given social system can vary considerably. However, as Watts and Dodds (2007) stress, empirical findings on the exact structure of interpersonal influence networks are scarce, and therefore, researchers use very basic network structures to study the fundamental way in which interpersonal influence aggregates to the social system level. The eight-cell neighborhood used here (which is called a *Moore neighborhood*) is probably the most popular neighborhood configuration in cellular automata applications, and it has been successfully used to describe a variety of social processes. In the diffusion-of-innovations paradigm, there are two communication factors that affect the transition of individuals from state “0” to state “1”:

- External factors: Some probability a exists such that in a given time period, an individual will be influenced by external influence mechanisms such as advertising, mass media, and other marketing efforts, to adopt the innovative product.
- Internal factors: Some probability b exists such that during a given time period, an individual will be affected by an interaction (e.g., word of mouth) with exactly one other individual who has already adopted the product.

The externalities effect: Threshold levels are introduced into the model as follows. The

number of previous adopters affects individual utility such that a given consumer's adoption depends on her individual threshold level h_i . Individual thresholds and personal networks are specified at the outset. Thus, individual adoption depends on two events occurring. First, the consumer is influenced to buy the product through product-related communications, and second, the overall adoption level surpasses that consumer's individual threshold level. Consistent with the collective action premise, the consumer adopts the product only if both events occur. Let the cumulative number of adopters at time t be denoted as $x(t)$, market potential as N , and individual threshold as h_i . If an individual is connected to $m_i(t)$ adopters belonging to her personal network, then the probability of adoption for that individual is given as follows:

$$prob(t) = \begin{cases} (1 - (1 - a)(1 - b)^{m_i(t)}) & \text{if } x(t)/N > h_i \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

A heterogeneous distribution and personal networks are specified at the outset; that is, each individual in the grid is assigned a particular value of h_i and has a well-specified personal network. A few points are worth noting regarding the above approach. First, since Granovetter's (1978) seminal work in disciplines such as sociology and communication, threshold models have been used to model a variety of phenomena, including the basic diffusion process. In these cases, the assumption is that an individual adopts an innovation only when a certain number of others, sufficient in number so as to surpass her threshold, have already done so (Deffuant, Huet & Amblard, 2005; Valente, 1995).

In contrast, *cascade models* such as the one used here (Leskovec, Adamic & Huberman, 2007) take a stochastic approach that follows the basic diffusion-of-innovations Bass model (1969) and its extensions. Under this approach, in each period, a customer has a certain probability of adopting communications with her previously adopting peers or in response to

marketing efforts. Here, we use a threshold model for the network effect yet maintain diffusion based cascade approach, as the latter offers a number of advantages for our case. First, it incorporates external effects such as advertising that are not traditionally part of the threshold adoption approach. Second, it allows a more realistic stochastic approach, while the adoption threshold is deterministic. Third, it follows a well-established research tradition in marketing, which also allows us to build on past research when setting up and calibrating model parameters. Still, we expect that the basic results we present will not change dramatically even with a diffusion-as-threshold approach, especially given simulation findings that show similar results of the two approaches (Watts & Dodds, 2007).

The second point to note relates to the reference group for the network effect. We here follow a global approach toward externalities. As discussed above, the global approach applies to a wide range of cases, including indirect effects, competing standards, and many cases of direct externalities. It is also consistent with past social threshold models of network externalities (Allen, 1988; Granovetter & Soong, 1986) and with much of the externalities modeling literature in general, including studies that deal with direct externalities (Economides & Himmelberg, 1995).

In contrast, word of mouth demands actual communication, not merely an assessment of the number of other adopters. While people may talk with many more people today via online communication, even in the so-called Internet Age, word of mouth is predominantly an offline phenomenon (Keller & Berry, 2006). Therefore, modeling word of mouth via local effects seems appropriate. Note, however, that some direct externality goods are more local in nature, and we further consider this fact in our discussion.

A third issue relates to the role of social inference, i.e., social signals that individuals infer

from the adoption of an innovation by other adopters. In addition to word-of-mouth and network effects, prior literature suggests that social inference may play an important role in the contagion processes that characterize the growth of new products (Peres, Mahajan & Muller, 2008; Van den Bulte & Stremersch, 2004; Van den Bulte & Lilien, 2001). Social inference is evident, for example, in the case of fashion items, as the number of other users plays a major role in the utility consumers derive. While social inference is not directly modeled in our approach to network externalities, clearly there are similarities, since in both cases consumer utility is a function of the number of other adopters. In fact, some social threshold modeling has suggested that status-seeking should be modeled in a manner similar to network externalities (Granovetter & Soong, 1986), and so our results provide insight regarding the growth of status-based goods as well. An important difference, however, is that for status products, we may expect more than a single threshold. Because of the need for uniqueness (Simonson & Nowlis, 2000), if the number of other adopters surpasses an upper threshold (i.e., the number of other adopters is too large), it will reduce the utility for some potential adopters. The difference between the processes that include one as opposed to two thresholds is an intriguing topic for research, yet it is beyond the scope of this paper.

Comparing growth processes. In order to compare growth processes with and without network effects, we must define a one-dimensional measure that will summarize the difference. Since any change in a growth pattern can have critical economic consequences for an industry, we chose to express our measure as the ratio of the NPV of the growth process with and without network effects. Thus, we compute the NPV for the non-externalities case and for the externalities case using a 10% discount rate per period, which is a reasonable yearly rate for many markets and fixed profit margins. The percentage ratio will serve as a proxy for the difference in the adoption

process. To minimize the random effects due to the particular realization of the stochastic simulation, we ran the program ten times for each set of parameters and then averaged the result. The dependent variable used in the rest of the paper known as the *NPV Ratio* is the average ratio of the NPV of the network externalities case to the non-network case. Hence, if the result of the NPV Ratio is 50% for a certain set of parameters, it means that the monetary value of the growth process of the network good was one half that of a non-network good with the same parameters based on the average of ten runs.

The Distribution of Thresholds. An important input for this modeling approach relates to the distribution of thresholds in the population. Much of the threshold modeling literature has implicitly or explicitly assumed that thresholds are normally distributed in the population (Valente, 1995). Since the normal distribution may be negative, it has been suggested that “negative” thresholds can be assumed to be zero (Granovetter, 1978). Unfortunately, there is scant empirical evidence regarding threshold distributions, since few attempts have been made to empirically measure thresholds.

While threshold modeling has served as a major tool in the collective action literature, nearly all studies have been based on either analytical assessment or simulations, with rare examples attempting to infer thresholds from indirect behavioral data (Taub, Taylor & Dunham, 1984) or direct survey data (Ludemann, 1999). Here, we follow much of the literature and assume the basic distribution used in the threshold modeling literature (Granovetter, 1978): a truncated normal distribution with mean μ and standard deviation σ . In addition, we examine a more general case with a Beta distribution that enables us to introduce skewness. The basic results were generally similar, and for simplicity, we report the normal results. While our focus here is not on the empirical derivation of the threshold distribution, in the discussion section we report

on a further exploratory experiment we conducted that measures thresholds. The results we obtained generally support the type and range of parameters we use here.

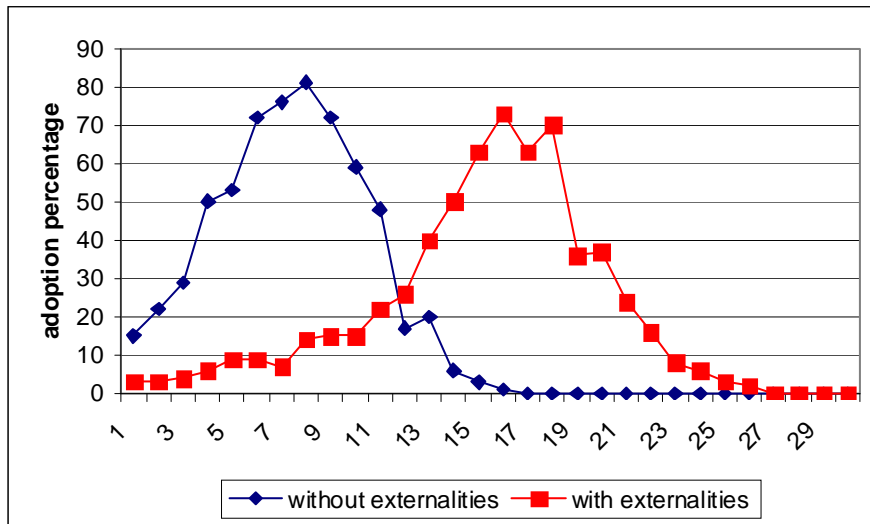
4. Market Growth in the Presence of Collective Behavior

We conducted a cellular automata experiment to examine the effect of change in the model parameters on the NPV. All combinations of the parameters were analyzed using a full factorial design experiment. Hence, for the normal distribution case, each of the four input variable parameters (a , b , h , and σ) was manipulated at five levels to produce $5^4 = 625$ total growth patterns. We used a social system of 625 individuals and examined 30 periods for each run. Since internal and external effects represent probabilities, their absolute value range determines the magnitude of a “period”, which is of less interest to us. Rather, our interest lies in the relative values of the parameters analyzed. Consistent with the previous literature as specified above, we set the individual-level marketing efforts effect at a lower range than that of the individual-level word of mouth effects. See Goldenberg, Libai, and Muller (2001, 2002) for further discussion on the parameter range for an individual-level cellular automata growth model like the one used here. Parameter ranges were set as follows.

a - external influence parameter	0.005 – 0.05
b - internal influence parameter	0.05 – 0.25
h - mean of the threshold distribution	1% – 20%
σ - standard deviation of the threshold distribution	$h/2 - 5h/2$

Figure 2 depicts the adoption curves with and without network externalities with a normal distribution for the threshold with the parameters $a = 0.02$, $b = 0.1$, $h = 10\%$, and $\sigma = 20\%$. The delay caused by network effects is apparent. Here, the NPV for the network externalities case was 51.6% of the NPV for the non-externalities cases.

Figure 2 - Adoption curves with and without network externalities



Taking this normal distribution as an example, when looking at the full sample of parameters, the average value of the NPV Ratio was 0.45 with a standard deviation of 0.27. This means that on average, network externalities caused a loss of over half of the discounted profits of the growth process. In more than 83% of the cases, the industry lost more than 25% of the discounted profits, and in 27% of the cases, it lost more than 75% of the discounted profits due to the effect of network externalities on the growth rate. In all cases, we saw a chilling effect of network externalities on profits. These results led us to the following conclusion:

Effect 1: Network externalities induce a possibly substantial *chilling effect* on new product growth and consequently on profit.

Exploring the effect of the various communication and threshold distribution variables on the NPV Ratio is done using an OLS regression; results are reported in Table 1.

Table 1 - Regression with the NPV Ratio as the dependent variable

	Standardized value
<i>a</i> - individual marketing efforts influence	0.40
<i>b</i> - individual word-of-mouth influence	0.14
σ/h - variability of threshold distribution	0.63
Adjusted R²	0.57

Independent variables are log transformed; all coefficients are standardized with p-value < 0.001 for all coefficients.

For the independent variables, we used the two communication parameters *a* and *b* and a variability parameter, which is the ratio of the standard deviation of the threshold distribution to the mean. This use of variability is acceptable when the effect of the variance of the distribution depends on the mean of the distribution (Snedecor & Cochran, 1980), which is relevant in our case. When the mean is high, changes in the standard deviation may have less effect on the number of adopters, especially in the early stage. Due to the possible nonlinear effects of the diffusion parameters on the NPV Ratio (Goldenberg, Libai, Moldovan & Muller, 2007), we use a lognormal configuration. Thus, the independent variables are the natural log of *a*, *b*, and variability. We note two key outcomes based on Table 1. The first relates to the variability of the thresholds, which emerges as an important influence on profitability. Recall that the dependent variable in question is the ratio of the NPV with network effects to the ratio without network effects. Thus, the higher this number is, the weaker is the effect of network externalities on the monetary consequences of growth. From Table 1, we infer the following results:

Effect 2: The larger the variability in the distribution of thresholds in the population is, the weaker is the effect of network externalities on growth.

The reasoning behind this result is not straightforward. Note that a larger variance in the threshold distribution has two effects. Some consumers early in the process will have lower

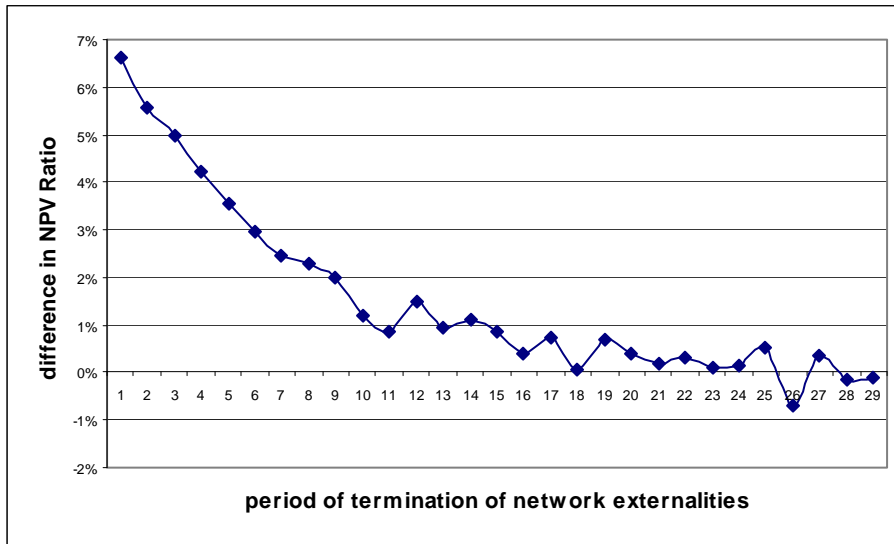
thresholds, while some consumers in the later stages will have higher thresholds. However, this result can be attributed to a phenomenon that dominates the effect of network externalities on new product growth, i.e., the asymmetrical influence of network effects on the early period of new product growth as compared to the later period. Due to the contagious nature of the diffusion of innovations, only after a certain number of early adoptions does the process take off. Thus, the effect of each member of this initial group is disproportional compared to that of later adopters. Therefore, any delay in this early period has a strong negative effect on growth.

In addition, while consumers can be theoretically affected by word of mouth and marketing efforts in each period, the adoption probability is low in the early periods due to the low number of previous adopters. Thus, the loss of time due to the blocking effect of network externalities is greater. With greater variability, the larger number of consumers at early stages with very low thresholds has a strong effect on the diffusion rate. This asymmetry can be seen in another aspect of Table 1, that is, the strong effect of advertising parameter a as compared to internal influence b . Since external effects play more dominant roles during the early phases of the diffusion process and internal effects play more dominant roles after takeoff (Van den Bulte & Stremersch, 2004), this phenomenon may suggest that the early period affects the NPV Ratio.

To better see the asymmetrical effect of the early period, we conducted the following analysis. We ran a cellular automata process in which the network externalities effect was terminated at various stages of the diffusion process. Hence, at some period labeled the termination period, all thresholds are set to zero. At first, the process was terminated in Period 1, then in Period 2, and so forth. For each case, we examined the NPV Ratio. Hence, the difference in the NPV Ratio, for example, between the NPV when externalities were terminated in Period 1 and the NPV when they were terminated in Period 2 allowed us to examine to what extent

externalities affect profits at various stages of the process. We conducted this experiment for a random sample of 30 parameter combinations within the parameter range we examined.

Figure 3 – Difference in NPV Ratios when network externalities terminate at various periods



As expected, the results suggest that network externalities play a considerably more important role in the beginning of the process than they do later on. To see this, consider Figure 3, which presents the change in the NPV Ratio from period to period as a function of the period in which the network externalities effect was terminated. It clearly shows that network externalities matter much more in the early stages than they do later on. We summarize this result as follows:

Effect 3: Network externalities have a stronger effect on profitability early in the product life cycle than they do in later periods.

5. An Aggregate-Level Analysis of Network Effects: Empirical Cases

While agent-based models enable us to understand how an individual-level phenomenon becomes a market-level phenomenon, one of the challenges of this approach is tying it to empirical data. One way to do so is to show that the results from the agent-based model are consistent with the aggregate-level data that are typically more available for analysis. In order to address this issue, we investigate a fully connected social network and thus extend the Bass

model. In the next section, we turn to an aggregate analysis of how network externalities affect growth and profitability by using data from five new product introductions coupled with a diffusion model that explicitly takes network externalities into account.

When making the transition from agent-based models of new product growth to an aggregate diffusion model, one might ask about the possible ways to demonstrate the relationships between the two. Following the increasing use of agent-based models to study growth, relating such models to aggregate-level data or latent data structures is becoming a topic of considerable interest to researchers (Garlaschelli & Loffredo 2008; Toubia, Goldenberg & Garcia, 2008). Recent studies in this area have mathematically demonstrated that if a homogenous population and large market potential are assumed, agent-based models are equivalent to the discrete version of the Bass model (Fibich, Gibori & Muller, 2008; Goldenberg, Lowengart & Shapira, 2008; Toubia, Goldenberg & Garcia, 2008).

It is harder to demonstrate a straightforward mathematical relationship between a given heterogeneity in a social network structure using the agent-based model framework and an aggregate one, and such a relationship will depend heavily on the network structure (Rahmandad & Sterman, 2008) with local social network-based growth. Yet studies on network-based growth processes such as cellular automata (Sarkar, 2000) suggest that they describe aggregate growth processes well. Our aim here is to demonstrate that the results derived using an agent-based model do not change when a more restrictive, aggregate-level model is used with market-level data. The model also enables us to compare the growth of various products and understand for the basis for this difference.

We apply our approach to five cases of new product introduction in the US that have robust externality effects, namely, fax machines, Citizen Band (CB) radios, cellular phones, DVD

players, and CD players.

In order to facilitate aggregate analysis, consider the fax machine as a well-known example of product growth influenced by network effects. The growth of fax machines in the US from the mid-1960s to the early 1990s was characterized by a slow start and a consequently long left tail followed by a fast takeoff. While a slow start of a durable is not surprising, a left tail of more than 20 years followed by such a sharp takeoff is not common, especially given that post-WWII introductions of durables typically had a shorter time to takeoff (Golder & Tellis, 1997).

One explanation for this pattern of growth for the fax machine could be network effects. It is clear that network externalities were not the only factor changing consumer perceptions over time. For example, as with most other durables, the growth history of the fax machine was characterized by a price decline and product improvements. However, the fax machine is often used in both the popular press and academic literature as an example of a product in which network effects played a major role in the consumer adoption decision process (Economides & Himmelberg, 1995).

While individual-level data on the penetration of these products are not available, we might nonetheless be able to examine the penetration of these products using an aggregate-level model. To this end, we use a changing market potential framework for product growth (Mahajan & Peterson, 1979). In the spirit of the threshold modeling approach, we incorporate the network effect by making market potential at any given time a function of the number of previous adopters and the distribution of thresholds in the population. Following our empirical analysis, we postulate that individual thresholds are distributed normally in the population with mean and standard deviation of h and σ , respectively, that is, with a cumulative distribution function $G \sim N(h, \sigma^2)$, where h and σ are measured as a percentages of the total market potential N . As

before, a “negative” threshold means that no previous adopters are needed for adoption.

Given this configuration, assume that at any given point in time t , $N(t)$ consumers have adopted. Taking the network effect into account, the market potential is comprised of only those consumers whose thresholds are lower than $N(t)$, since crossing the threshold is a necessary condition for adoption. Thus, the aggregate adoption function is:

$$dx/dt = \left(p + q \cdot \frac{x(t)}{N(t)} \right) \cdot (N(t) - x(t)), \quad (2)$$

where $x(t)$ is the cumulative number of adopters up to time t ; p and q represent the effects of external influence and internal influence, respectively; and the changing market potential is given by:

$$N(t) = \text{prob} \left(H < \frac{x(t)}{N} \right) \cdot N \text{ and } H \sim N(h, \sigma^2). \quad (3)$$

Note that the approach is similar in spirit to the agent-based model in that the threshold effect is global. One difference is that as with aggregate diffusion models in general, the word-of-mouth effect is global, whereas in the agent-based model, it is local. Under this approach, we have two more parameters to estimate as compared with the basic Bass function, namely, h and σ . Note that the basic Bass model is nested within this modified Bass model. In order to achieve the Bass model from Equations (2) and (3), one has to set $h = \sigma = 0$. It follows that $\text{prob}(H < x(t)/N) = 1$, and thus, $N(t) = N$. Equation (2) now becomes identical to the Bass model.

We next estimate the model parameters by using Equations (2) and (3) and the NLS estimation algorithm. We first provide a short description of each innovation and then present Table 2, which summarizes the estimation results.

Fax machines: As mentioned earlier, fax machines were introduced in 1965 in the US and

took off more than 20 years later. The direct externalities of the fax machine case are well known and documented; see Rohlfs (2001). The data considered here include annual unit sales in the US during 1965-2006 (source: eBrain Consumer Electronics Market Research Data).

Citizen Band radio: The CB radio is a two-way communication radio that a civilian (as opposed to police or military) can use to communicate with any other CB radio operator. The CB radio industry began in 1958, when the FCC formed the basis for the Citizen Band as it is now known. It then took about 17 years for CBs to takeoff. The data considered here include annual unit sales in the US during 1958-1982 (source: various issues of *CB Yearbook*, FCC reports, and the Electronic Market Data Book).

Cellular phones: Mobile phone services were commercially launched in Scandinavia in 1981 and since then have become a part of the everyday lives of over 49% of the world's population in 211 countries. The data considered here include sales of cellular phones, including analog, dual-band, and PCS types (GSM, TDMA, CDMA and so on), in the US during 1984-2008 (source: eBrain Consumer Electronics Market Research Data).

DVD players: DVD players were launched in 1997 on the US market following a delay of at least three years; moreover, they were introduced with two competing standards. Adoption grew fairly rapidly following introduction. The indirect nature of network externalities via market mediation in the DVD case is clear. The number of users of DVD players influences the number of DVD titles available in rental outlets. The data considered here include annual unit sales in the US during 1997-2008 (source: eBrain Consumer Electronics Market Research Data).

Compact Disc players: CD technology was developed by Phillips in 1979 and introduced in the US in 1983. The indirect externalities of this industry are well documented (Le Nagard-Assayag & Manceau, 2001; Shy, 2001; Gandal, Kende & Rob, 2000). The data considered here

include annual unit sales in the US during 1983-2005 (source: eBrain Consumer Electronics Market Research Data).

Our aim is to observe the chilling effect as well as the threshold distribution effect in the aggregate data. We therefore look at a number of variables for each product as follows:

Heterogeneity of the threshold levels in the relevant population: Following the above discussion, we expect that heterogeneity in threshold levels will result in a strong chilling effect. We ran the regressions as described in Equations 2 and 3, and for heterogeneity, we used the variability parameter of the threshold level σ/h . We expect the chilling effect to be more pronounced in cases in which the ratio is lower.

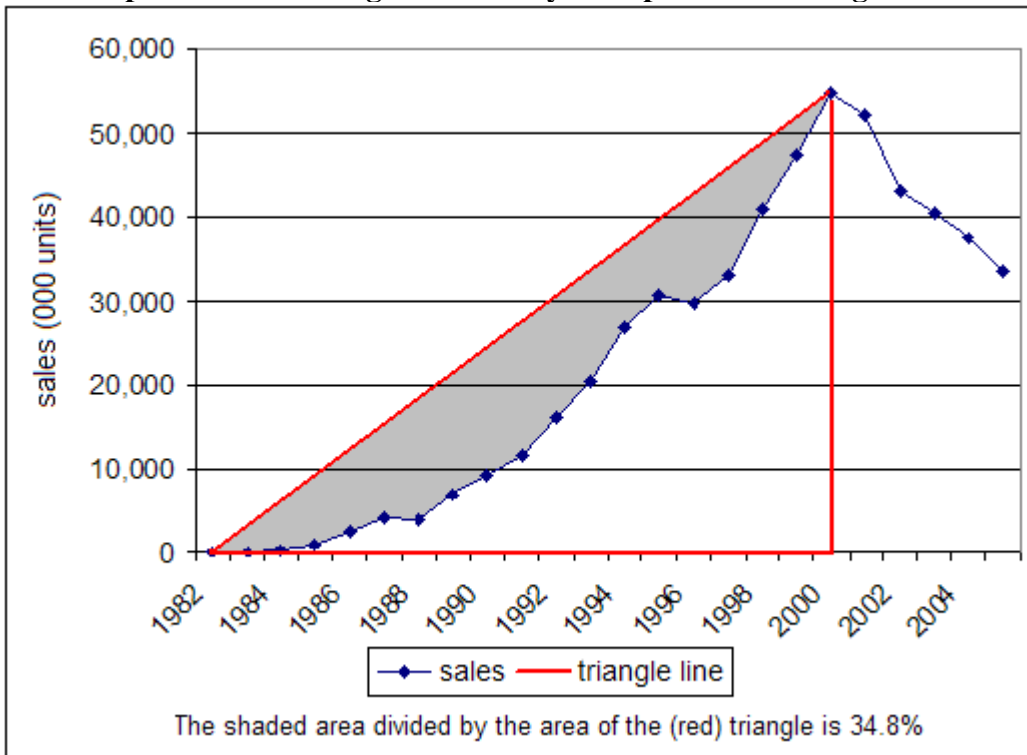
The degree of network externalities: Recently Srinivasan, Lilien, and Rangaswamy (2004) provided a ranking of the degree of network externalities for a number of durables based on the ratings of various judges. Rankings ranged from 2 for a product with low network effects to 14 for a product with very high network effects. Among the five products we use, CB radio is not included in this list. From a network externalities point of view, the CB radio is an obvious case of a communication product that should exhibit high network effects. Similar to the fax machine, in the absence of other adopters, the product has very little utility. We thus evaluated its degree of network externalities as similar to that of fax machines, as assessed by Srinivasan, Lilien, and Rangaswamy (2004).

The chilling factor: We computed NPV ratios for each product with and without network externalities. First, we computed the NPV using one unit of profit per product and a 10% yearly discount rate. For the non-externalities case, we used p and q derived from the aggregate analysis but with threshold levels of zero. Recall that the NPV Ratio is the NPV of the cash flow with externalities divided by the NPV of cash flow without externalities. Since a higher NPV Ratio

weakens the chilling effect, we define the chilling factor as 1 minus the NPV Ratio.

The degree of hockey stick patterns of growth: One way to capture the non-monotonic growth phenomenon under analysis is to look for patterns of growth characterized by a long left tail and then a fast takeoff. Such a growth pattern is sometimes termed a “hockey stick” pattern of growth (Bayus, Kang & Agarwal, 2007). Consider Figure 4, which shows the growth of CD players in the US. Note the straight line that connects two points, namely, the time at which the process began (0) and the time of maximum sales in 2000.

Figure 4 – Computation of the degree of hockey stick pattern for the growth of CD players



As a proxy for the degree of hockey stick patterns of growth, we can use the area between the straight line connecting the function at these two points and the real data. We express this term as a percentage of the area under the line (the red triangle of Figure 4) analogously to the Gini coefficient. If one thinks about a phase transition, i.e., a point of time at which the process passes from one phase to another, then the ultimate phase transition is of course a step function. For such

a function, the measure will take the value of 1. At the other extreme, the measure will be zero for a linear function. For the rest of the growth patterns, the degree of hockey stick growth will fall between these two bounds. One should also note that the measure should be taken with care, as the growth function is not necessarily convex, as can be seen in Figure 4.

The results are presented in Table 2 and are generally consistent with our expectations. They indicate that high network externalities are generally consistent with low heterogeneity in threshold levels, a high chilling factor, and a high degree of hockey stick growth.

Table 2: Chilling factor and related variables for five network goods

Product	Network externality	Threshold heterogeneity	Chilling factor	Degree of hockey stick
Fax machines	10.6	0.33	95.1%	62.9%
CB radios	10.6	0.34	79.5%	76.6%
Cellular phones	10	0.68	86.1%	46.7%
DVD players	9.4	0.80	34.8%	25.2%
CD players	9.3	1.35	55.2%	34.8%

6. Discussion and Implications

In this paper, we focused on a basic, negative effect of network externalities on the growth rate of new product, and, consequently, on the associated NPV of this effect. Due to the sizeable effect of growth rate on customer equity and possibly the valuation of firms (Libai, Peres & Muller, 2009a), this aspect of network externalities can have considerable financial implications for firms. We find that while the effect is more pronounced in the early stages of the product’s life, it may be less harmful when the variability in the individual threshold distribution is high.

To demonstrate the magnitude of this effect, consider again the case of the fax machine.

One might wonder what the expected penetrations of fax machines would be if network effects were not present. Regarding fax machines, imagine a case in which the government had allowed all citizens and businesses to conduct all government-related communications by fax at an early stage of growth. In such a case, the network externalities effect would have decreased substantially. Following a similar method as that used to derive the chilling effect for fax machines (see above), we examined the expected penetration without externalities.

Figure 5 – Fax penetration with and without network effects

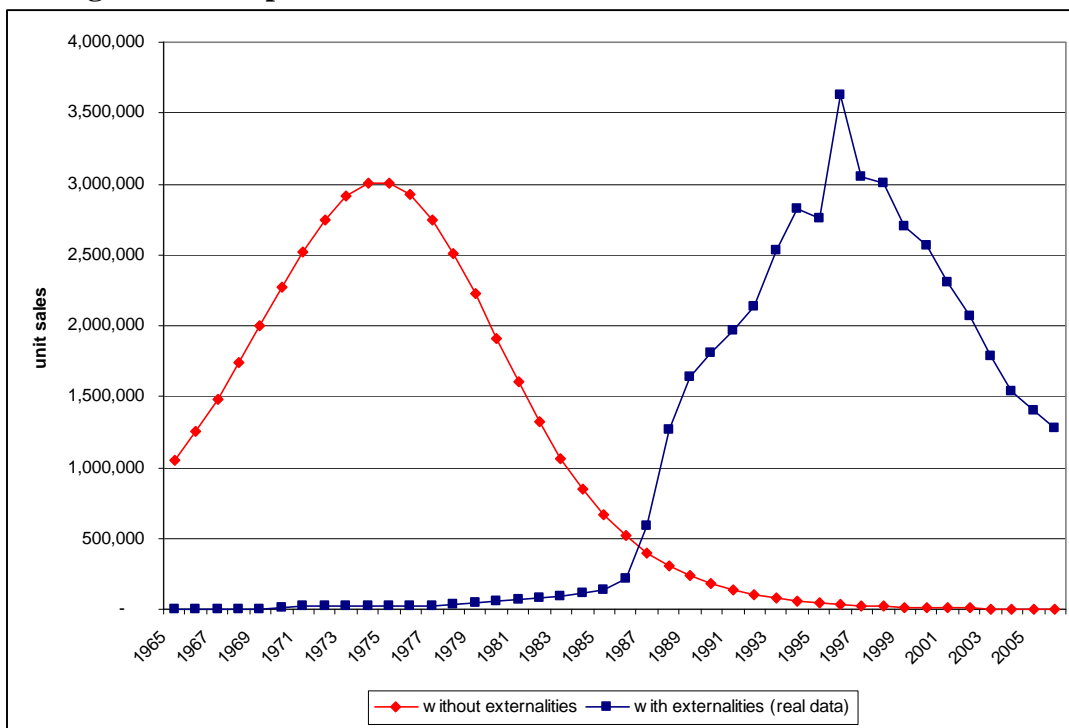


Figure 5 presents the actual growth of the fax machine and its growth in the case in which no externalities exist; also, note its similarity to Figure 2, which presents an agent-based simulation. In such a case, nearly all penetration would have occurred before 1985, i.e., before the fax’s actual takeoff. Using the prices of fax machines in the various time periods as reported by the CBEMA (1994), we can estimate the actual loss. For example, the non-discounted loss due to thresholds during 1965-1985 was \$42 billion (in 1994 values). Of course, other situations

in which only part of the externalities effects vanishes may have been at work, in addition to other dominant factors, such as price and quality, that halt the adoption process. However, these figures demonstrate the magnitude of monetary loss due to network externalities on growth speed in this and other cases.

The ubiquity of the chilling effect: Given that later growth may accelerate more rapidly due to the bandwagon effect, a question arises as to whether we can identify situations in which later rapid takeoff compensates for an early slow start to that a firm can enjoy the overall network effects. We could not identify such cases. First, as reported above, across a wide range of scenarios in the agent-based model, we consistently observed a chilling effect on profits. Second, we ran a simulation on the aggregate-level diffusion model in which we proposed varying diffusion parameters p and q as well as the threshold distribution, and the results were the same.

Given the above analysis, one might wonder about the basis for the popular perception that network externalities drive fast growth. The explanation is likely related to the fact that observations on the subject are made closer to takeoff, when indeed externalities help to drive fast growth. This is not surprising since at that time, more competitors join the market, and the product begins to capture more media attention. For firms that join at that stage, the bandwagon effect may be good news in terms of growth rates. However, looking at the entire process from early on from which the entire growth process has to be discounted, the picture is different.

Competitive considerations and the chilling effect: Research on network externalities has been understood to effect growth rates in the context of competition, especially with respect to competing standards (Farrell & Klemperer, 2006). A pioneer has an incentive to boost the speed of growth in order to capture a market share that will increase the utility of future and current

customers, possibly situating the new product as the eventual standard. Hence, firms may want to invest early in R&D and deliberately introduce new incompatible technologies early on (Kristiansen, 1998), or they may introduce low pricing to deter the entry of a competitor (Fudenberg & Tirole, 2000).

Accordingly, our results offer two main insights. First, we demonstrate the financial role of time regardless of competition, as the chilling effect also occurs in the case of a market monopolist. Such a monopolist is motivated to increase the speed of diffusion, which demonstrates the need to set realistic growth and financial expectations given network effects. Also, we highlight the dark side of network externalities for a market pioneer. While network effects provide a competitive advantage over later entrants, they also slow cash flow, thereby potentially creating major financial disadvantages. This effect may contribute to high failure rates for pioneers in network markets (Srinivasan, Lilien & Rangaswamy, 2004) and should be taken into account when considering pioneering advantages as well as when planning market strategies in the presence of network externalities.

The impact of product type on growth: An interesting issue to consider relates to the variability in the chilling effect among products. Price is one factor (see the Appendix), as the lower the product's price is, the more easily thresholds may be passed, and so externality factors play a smaller role. Another source of variability relates to the degree of externalities. As discussed above, one might expect that if externalities play a larger role in customer decision-making, then the average threshold required for adoption should increase. A third source of variance may stem from the type of externality. We might expect that competing standards may on average invoke a chilling effect that is stronger than that of indirect externalities for two reasons. First, the risk people take in the context of competing standards is higher, since a wrong

choice may result in a product that becomes useless in a short time. This contrasts with indirect externalities, as consumers may merely have to wait a while until there is enough software to surpass their individual threshold. This means that in the context of competing standards, individual thresholds are likely to be higher.

Second, in the case of indirect externalities, marketers can more easily control the provision of software to encourage users to adopt earlier and thus mitigate the chilling effect. This is not the case for competing standards, as utility is not under the firm's control, and so people will wait longer before "jumping on the bandwagon". This result is consistent with findings on the slower growth rates of product categories with competing standards (Van den Bulte & Stremersch 2004, 2006).

Of course, if the winning standard is determined early due to exogenous factors, the chilling effect may be weak. As in the case of competing standards, in the case of direct externalities firms will have a harder time controlling the chilling effect, since they do not have a straightforward market mechanism to help potential adopters surpass their individual thresholds. Therefore, one might expect a stronger chilling effect. Still, firms may manipulate this process via mechanisms such as price. This might explain the tendency of marketers to offer free or low-cost Internet communications products such as freeware and build on other sources of income. For such products, the chilling effect may be rather weak, especially with more costly and older products like the fax machine and CB radio we considered here.

The local effect of direct externalities: While we assumed a global network effect in our model, we noted that for some direct network goods, such an effect might be mostly locally driven (see Tucker 2008). One might wonder if the chilling effect we present holds in such a case. To explore this issue, we conducted a cellular automata exploratory experiment similar to the one

reported above, but we replaced the global externalities effect with a local one. That is, if an individual has a 50% threshold, then instead of requiring 50% of the entire social system to adopt a product, 50% of the local eight-cell social network would be required. In general, we observed a chilling effect, but we saw no effect with very small local thresholds, as discussed below.

The relationship of global to local effects is not clear-cut. In some cases, local externalities had a stronger chilling effect, but in some cases, the effect was weaker. Nonetheless, an interesting observation could be made. In the lower percentages of the threshold distribution, the global setting had a stronger chilling effect, while for higher percentages, the local setting had a strong effect. The reason is that if an individual's local threshold is low enough, a single adopter in that individual's personal network was enough to surpass it. Since this adopter is also needed for a word-of-mouth effect, the threshold can not play a true chilling role, and the effect is not noticeable. On the other hand, for threshold distributions with high means, we saw that the required number of adopters may be larger in the personal network. The precise difference between local and global externalities effects is an intriguing question, and we see an exploration of this issue as an interesting avenue for future research.

The distribution of thresholds: Given the impact of the threshold distribution on sales, growth marketers are naturally be interested in learning how they can assess the distribution. However, while threshold distribution has played an important role in the collective action literature, there are few empirical methods for assessing thresholds. Empirically measuring thresholds in the context of new product growth process is particularly complex due to interactions of the utilities of actual and potential adopters as a source of personal information. While a full exploration of empirical methods to research thresholds is beyond our scope here, we did attempt to offer some preliminary suggestions on this topic.

In our attempts to directly measure network effect thresholds, we found that respondents had difficulty separating word-of-mouth from externalities. Even when consumers were explicitly told that they already possessed positive information about a network good, debriefing revealed that the number of other adopters that they demanded in order to adopt a product was related not only to externality effects but also to word of mouth from other adopters.

In order to separate network effects from word-of-mouth effects in a precise way, a two-phase survey was designed. In the first phase, respondents were given a scenario regarding the penetration of a new product without externalities. They were then asked to reveal the percentage of their friends and acquaintances that would have to adopt the product before they themselves would adopt it. In the second phase, we added an externalities feature to the same product; we introduced a videoconferencing component that requires adopters with the same kind of phone. We then again asked about the number of other adopters needed to purchase the product. The response to Phase I of the questionnaire represents how other adopters affect potential adopters in terms of risk reduction, while Phase II includes this risk reduction in addition to network effects. Hence, the difference between the two phases can serve as a proxy for the need for other adopters due solely to network externalities. We used these methods to present undergraduate and graduate students with various scenarios regarding the penetration of network products, including (1) an advanced fax machine, (2) an advanced cellular phone with picture-sending capability, (3) videoconferencing, and (4) an advanced mail program. Thus, we had four different studies with a total of 180 respondents.

We found in all four studies that the externalities distributions were truncated bell-shaped. In one study, this distribution was symmetrical, and thus, a truncated normal distribution is a reliable working assumption. In the other three cases, the distribution was somehow skewed. In two

studies, leftward skewness was evident, and in one study, moderate rightward skewness was observed. Overall, these results support the threshold distribution used in this study. However, we believe that given the importance of threshold distribution presented herein, future empirical research is needed to gain insights on how to assess the distribution of thresholds and the shapes of the distribution under various market scenarios.

7. Limitations and Conclusion

There are several limitations to this paper that could be addressed in future research. The aggregate diffusion process that we use here is subject not only to demand-side effects but also to supply-side effects. For example, the degree of chill depends on the extent to which a supplier of the product, namely, either a monopolist or a competitive firm, is able to internalize the externality and appropriate the revenue that arises due to the externality (Katz & Shapiro, 1994). The issue of supply constraints has been investigated in a dynamic growth context, though not when network effects were present (see for example Nunn & Sarvari, 2004 or Jain, Mahajan & Muller, 1991). If one considers a network good with a pronounced hockey stick effect of over 60% such as the fax machine, then it is clear that when takeoff finally occurs, production and distribution issues will dominate the agenda of management unless careful planning is carried out well ahead of time when demand is relatively flat and growth is anemic.

The model we use in this paper is described in Equation (1) in terms of an agent-based framework and in Equations (2) and (3) using an aggregate model; our framework does not specify an exact behavioral premise that relates network externalities to threshold-based customer decision-making. In the Appendix, we specify such a utility-based model that relates threshold levels to network externalities via two alternative models, namely, additive and multiplicative models. Though we opt for the latter rather than the former, behavioral studies that investigate

individual utility in this respect are certainly called for.

One might also wonder if different network structures might induce differential effects on the spread of diffusion. In this case, the observed NPV Ratios might vary by network structure. While we acknowledge that the formation of personal networks in a given social system can vary considerably, there is a long branch of research that suggests that cellular automata, despite its simple network structure specification, captures complex social phenomena well (Sarkar, 2000). In addition, as Watts and Dodds (2007) have mentioned, empirical generalizations on the exact structure of interpersonal influence networks are scarce, and therefore, researchers are encouraged to use simple network structures to study how interpersonal influence aggregates to the social system level. Moreover, from our experience, the results of cellular automata runs are not overly sensitive to perturbations in their basic formulations, except for the considerable effects of weak ties, which were not studied in this paper.

Overall, we see this paper as a starting point for studying the chilling effects of network externalities under various conditions and market structures. We believe such studies will fruitfully complement the existing literature, which has not focused on the temporal impact of network externalities and the monetary cost associated therewith. We found indications of a substantial financial effect that should be of considerable interest to managers, and we hope that these findings will trigger additional explorations of this important area of research.

Appendix: Network Externalities and Threshold Levels

The model we use in this paper, which is described in Equation (1) in terms of an agent-based framework and in Equations (2) and (3) using an aggregate model, does not specify the exact behavioral premise that relates network externalities to threshold-based customer decision-making. One could envision different models in this respect. In this Appendix, we present a utility-based approach in which an individual's threshold depends on the utility derived from the presence of other adopters as well as product features and price. Of course, other variations on the specific utility function can also lead to the threshold effect used in the market growth model. One such variation is discussed in this Appendix as well.

Let $u_i(a, x)$ be individual utility from the product, where a is the vector of the product attributes, and x is the cumulative number of adopters up to the current period. Suppose the utility of the individual from the product attributes (net of price) is given by a compensatory model of a standard conjoint analysis. If a_j and w_{ij} are the respective level and weight of attribute j for individual i , then an individual's utility from product attributes other than network externalities is given by:

$$A_i = \sum_j w_{ij} a_j \quad (\text{A1})$$

We further assume that the network externalities effect is multiplicative and of the form $(x/N)^{\delta_i}$, where N is the number of people in the social system. It thus is given by:

$$u_i(a, x) = (x/N)^{\delta_i} A_i \quad (\text{A2})$$

Hence, the utility from the product increases with the percentage of adopters, yet it is heterogeneous in the population through δ_i . For those individuals for which $\delta_i = 0$, network externalities are not a factor when making a purchase decision. If P is the price of the product, then the potential adopter decides to adopt the product if the following holds:

$$u_i(a, x) > P \quad (\text{A3})$$

A simple algebraic manipulation of Equations (A2) and (A3) reveals that an individual will adopt the product if:

$$(x/N) > (P/A_i)^{1/\delta_i} \quad (\text{A4})$$

This adoption equation allows us to define an individual threshold level denoted by h_i as the right-hand side of Equation (A4), that is:

$$h_i = (P/A_i)^{1/\delta_i} \quad (\text{A5})$$

The individual parameter h_i is thus the threshold level for consumer i so that the individual will adopt the product if $(x/N) > h_i$. Note that from Equation (A2), for the consumers for whom $\delta_i = 0$, utility is given by A_i , and thus, they are unaffected by the number of previous adopters. Therefore, the distribution of network externalities levels δ_i induces a distribution of threshold levels h_i and vice versa. Given a distribution of threshold levels, one can construct a distribution of network externalities levels.

Note that we have chosen a multiplicative formulation since it reflects the basic premise of our models. That is, our models rely on the collective action principle that the consumer adopts an innovation only if the level of adoption surpasses that consumer's individual threshold level. In a purely additive compensatory model, the one-to-one relationship between network externality and threshold levels will continue to hold. To see this relationship, suppose utility is additive in network effects, and thus:

$$u_i(a, x) = \sum_{j \neq k} w_{ij} a_j + w_{ik} (x/N), \quad (\text{A6})$$

where attribute k is the effect of network externality. Given price P , and following the same manipulation as above, the threshold in the compensatory model is given by:

$$h_i = \left(P - \sum_{j \neq k} w_{ij} a_j \right) / w_{ik}. \quad (\text{A7})$$

The difference between the two formulations in this Appendix is reflected in the treatment of those who buy at time zero when no previous adopters have yet purchased the product; that is, there are no network effects. In the multiplicative model, only those individuals with $\delta = 0$ would buy the product at time zero, while in the additive form, there will be consumers who buy at time zero with positive weight $w_k > 0$, though other attributes are large enough to compensate for the lack of initial adopters. The fact that the initial buyers are ill-identified in the additive model, together with the fact that it does not correspond well to the collective action framework, renders it less appealing as a model for network externalities. Note also that the additive form assumes a linear relationship, while the multiplicative form exhibits diminishing marginal benefits in the number of adopters if $\delta < 1$ (Swan, 2002).

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