# The Chilling Effects of Network Externalities

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# The Chilling Effects of Network Externalities


## 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 a slowdown effect on growth initially, because potential customers wait for other adopters to provide them with more utility before they adopt. In this study, we explore the financial implications of network externalities, taking the entire 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 can occur not only in a competitive scenario such as competing standards, but also in the absence of competition. Drawing on the collective action literature 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 show the "hockey stick" growth pattern, 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? Interestingly, despite the sizeable attention in the academic literature to the dynamics of network goods markets, the answer to this question is not obvious. Conventional wisdom suggests that network effects, or network externalities — wherein consumers' utility from the product depends on the number of other users — 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, initially 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 the innovation, as there are few other adopters (Farrell & Saloner, 1986). Therefore the growth of network goods may follow a two-stage process: slower diffusion initially with a very fast growth stage afterwards (Rogers, 2003). The question remains as to the overall effect on the time it takes an innovation to grow. The growth rate is of considerable managerial relevance due to the time value of money, as acceleration in growth speed can translate to a sizeable difference in the Net Present Value (NPV) of the innovation. However, little is known about the NPV impact of network externalities via the growth rate and the factors that drive it. This lack of knowledge is notable given the growing interest in optimal product strategies for network goods. Various market entries or reactions to market entry strategies for 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 effect of network externalities on new product growth rates and consequent profitability. To do so, we combine a classical diffusion model in the tradition of 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 respectively, and examine how market characteristics affect the difference. In a second stage, we present an aggregate diffusion modeling approach that enables an analogous analysis using market-level data. Note that consistent with diffusion research, all the analyses as well as the profitability measure are conducted at the industry level. The extension to brand level of any diffusion process, even without network externalities, while certainly worthwhile, is beyond the scope of this paper (e.g., Libai, Peres, & Muller, 2009a, 2009b).

Our work is consistent with recent calls for 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 indeed the bandwagon effect can 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 net present value. The result is consistent across a wider range of parameter values tested. 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, the weaker 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 growth rate, and then show how a threshold model can be combined with a classic diffusion setting using an agent-based approach to conduct an experiment comparing markets with and without network effect. Then we provide an aggregate-level approach, empirically examining 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 had a pronounced emphasis on the equilibrium reached in network markets rather than the dynamic path (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, suggest that introducing network externalities into a dynamic model of market growth "increases that speed at which market demand grows…" Rohlfs (2001, p. 56) suggests 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 externality 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 an 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 enough 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, the higher the utility of the product. In *indirect network effects*, such as hardware / software products, possible increase in utility occurs 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 with 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 it is clear what the winning standard is, and more importantly, which standard or platform will no longer be supported.

The precise dynamics of network externalities' impact on growth rate may be determined by the source of externalities examined. Past literature pointed to two types of effects in this regard: *local* and *global*. Under *global externalities*, a consumer takes into account the entire social system when considering the impact of the number of others on the 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 the joint effect is not trivial (Tomochi, Murata, & Kono1, 2005). This *reference group effect* probably changes among various kinds of externalities. For indirect externalities goods, 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 noting, as some standards have become dominant ***locally*** for long periods, for example, Apple with artists and designers, and Sony's Betamax videocassette format with broadcasters. In addition, recent network effects literature has gone beyond total number of users as the only characterization of network effects (e.g., 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 local utility from the number of others will drive adoption. Evidence for such effects has been largely based on geographical 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 Citizens Band (CB) radio, a product whose growth will be discussed later herein, much of the utility follows the ability to communicate with random others on the road or at travel sites. The same goes for many user-generated media sites and file-sharing sites wherein users enjoy the presence and contributions of others who are not necessarily part of their social system.

While the diffusion-of-innovations literature does not offer a straightforward approach to modeling the growth of a market for a network good (see Peres, Mahajan, & Muller, 2008 and Chandrasekaran & Tellis, 2005 for recent reviews), there have been efforts to incorporate network effect 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 effect, i.e., word of mouth and imitation, typically used to reduce both risk and search costs. Yet previous adopters also supply value through the increase in the utility of a network good. The diffusion of innovation modeling literature, specifically the Bass model (1969) and its extensions, generally do not separate the two, and a single parameter of internal influence is used to capture both the impact of interpersonal communications and that of 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: S/he has to be convinced via the communication process that the product is not risky and provides value, as in any other product; and s/he has to 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 *the proportion of the 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 wherein individuals engage in a behavior based on the proportion of others in the group already engaging in the same behavior (Yin, 1998; Macy, 1991; Granovetter, 1978). Threshold distribution has helped to explain how social groups move from individual-level behavior to collective action in areas such as strikes, riots, attendance at meetings, and migration (Granovetter, 1978).

Markets of network goods are suitable candidates for analysis using the social threshold approach because an adopter's utility from a product is directly affected by the number of others 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 others can be related to a threshold distribution in the population. While this model is not necessary for the following analysis (we assume that there is a distribution of thresholds in the population, and do not focus on the exact way thresholds evolve), it helps to understand that an individual's threshold will depend not only on the utility from the others' presence, 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 to examine issues related to new product growth (Delre, 2007; Goldenberg , 2007; Shaikh, Rangaswamy, & Balakrishnan, 2006; Garcia, 2005; Libai, Peres, & Muller, 2005). Cellular Automata modeling is a fundamental agent-based modeling technique that has been extensively used across disciplines to model social-based phenomena. We present herein a brief description of the methodology. 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 which is able to receive information and make decisions during consecutive, discrete periods. The cellular automata framework can be conceived of as a matrix of cells where each cell, representing a potential consumer, can take one of two states: "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 – 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 interpersonal influence aggregates to the social system level. The eight-cell neighborhood used here (labeled *Moore neighborhood*) is probably the most popular in cellular automata applications, and has been successfully used to describe a variety of social processes. Following 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 a single 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 by 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 by $x(t)$, the market potential by $N$, and individual threshold by $h_i$. If an individual is connected to $m_i(t)$ adopters belonging to her personal network, then the probability of adoption of that individual is given by the following:

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

A heterogeneity distribution and personal networks are specified at the outset (i.e., 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: Threshold models and adoption; the issue of the nature of the reference group for the network effect; and the role of status. Regarding the first, since Granovetter's (1978) seminal work in disciplines such as sociology and communication, threshold models have also 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 that surpasses her threshold have done so (Deffuant, Huet, & Amblard, 2005; Valente, 1995).

In contrast, *cascade model*s such as the one used here (Leskovec, Adamic, & Huberman, 2007) take a stochastic approach that follows the basic diffusion-of-innovations tradition in the spirit of the Bass model (1969) and its extensions. Under this approach, each period, a customer has a certain probability of adopting following communications with her previously adopting peers, or in response to marketing efforts such as advertising. Here we use a threshold model for the network effect, yet maintain the diffusion in a 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 a part of the threshold adoption approach. Second, it takes the 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 the diffusion-as-threshold approach, especially given simulation findings on similar results of the two approaches (Watts & Dodds, 2007).

The second point to note regards the *reference group* for the network effect. We have followed here the global approach of 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 work in general, including that dealing with direct externalities (Economides & Himmelberg, 1995).

In contrast, word of mouth demands actual communication, not merely assessment of the number of others. While people may talk with many more others today via online mechanisms, even in the Internet Age, word of mouth is predominantly an offline phenomenon (Keller & Berry, 2006). Therefore, modeling of word of mouth via local effects seems appropriate. Note, however, that some direct externalities goods are more local in nature, and we further consider this fact in the discussion. The third issue regards 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, where the number of other users plays a major role in the utility consumers derive therefrom. While social inference is not directly modeled in our approach, which focuses on network externalities, clearly there are similarities, since in both cases the consumer's 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 insights 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 is to surpass an upper threshold (i.e., the number of others is too large), it will reduce the utility for some. The difference between the two processes — one threshold, or two — is an intriguing topic for research, yet 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 in the two cases. Thus we compute the NPV for the non-externalities case and for the externalities case (using a 10% discount rate per period, a reasonable yearly rate for many markets and fixed profit margins), and their percentage ratio will serve as our 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, then averaged the result. The dependent variable used in the rest of the paper — 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 regards 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 have a threshold of zero (Granovetter, 1978). Unfortunately, there is scant empirical evidence regarding threshold distributions, as in general, few attempts have been made to empirically measure thresholds.

While threshold modeling has been a major tool of the collective action literature, nearly all studies have been based on either analytical assessment or simulations, with rare examples attempting to infer threshold from indirect behavioral data (Taub, Taylor, & Dunham, 1984) or asking individuals directly (Ludemann, 1999). Here we follow much of the literature and assume the basic approach of the threshold modeling literature (Granovetter, 1978), as well as a truncated normal approach with mean $\mu$ and standard deviation $\sigma$. We also examined 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 empirical derivation of the threshold, in the discussion we report on a further exploratory experiment we conducted that demonstrates an approach to threshold measurement. The results we obtained generally support the type and range of parameters we use here.

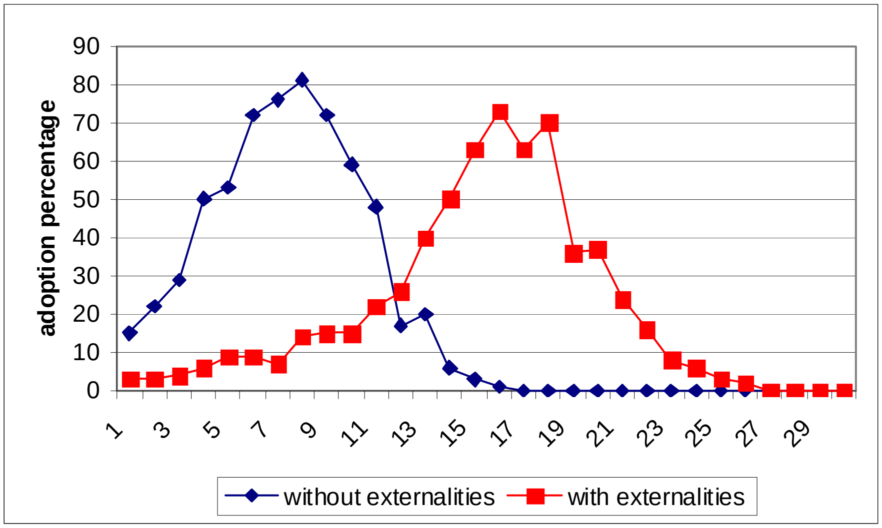
## 4. Market Growth in the Presence of Collective Behavior

We conducted a cellular automata experiment to examine the effect of change in the model parameters on NPV. All combinations of the parameters were considered in a full factorial design experiment. Hence, for the Normal Distribution case, each of the four input variable parameters ($a$, $b$, $h$, and $\sigma$) was manipulated on five levels, to produce overall $5^4 = 625$ 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 previous literature as specified above, we set the individual-level marketing efforts effect to be in 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 of the type 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% |
| $\boldsymbol{\sigma}$ - standard deviation of the threshold distribution | $h/2$ – $5h/2$ |

Figure 2 depicts the adoption curves with and without network externalities in one case of the Normal Distribution with the following set of parameters: $a$ = 0.02, $b$ = 0.1, $h$ = 10%, and $\sigma$ = 20%. The delay caused by the network effect is apparent. Here, the NPV of the network externalities case came up at 51.6% of the NPV of the non-externalities cases.

**Figure 2 - Adoption curves with and without network externalities**




Taking the Normal Distribution as an example, when looking at the full sample of parameters, the average value of 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:

**<u>Effect 1</u>: Network externalities induce a *chilling effect* — possibly substantial — 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 by using an OLS regression whose results are reported in Table 1.

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

| | Standardized value |
|---|---|
| ***a*** - individual marketing efforts influence | 0.40 |
| ***b*** - individual word-of-mouth influence | 0.14 |
| $\sigma/h$ - variability of threshold distribution | 0.63 |
| **Adjusted $R^2$** | 0.57 |

Independent variables are log transformed; all coefficients are standardized; 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. Such use of variability is acceptable where the affect 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 used a lognormal configuration. Thus, the independent variables are the (natural) log of *a*, log of *b*, and the log of the variability. We see two key outcomes from Table 1. The first relates to the variability of the thresholds, which emerges as an important influencer of profitability. Recall that the dependent variable in question is the ratio of NPV with network effects to that without them. Thus, the higher this number is, the weaker the effect of network externalities on the monetary consequences of growth. From Table 1, we infer the following results:

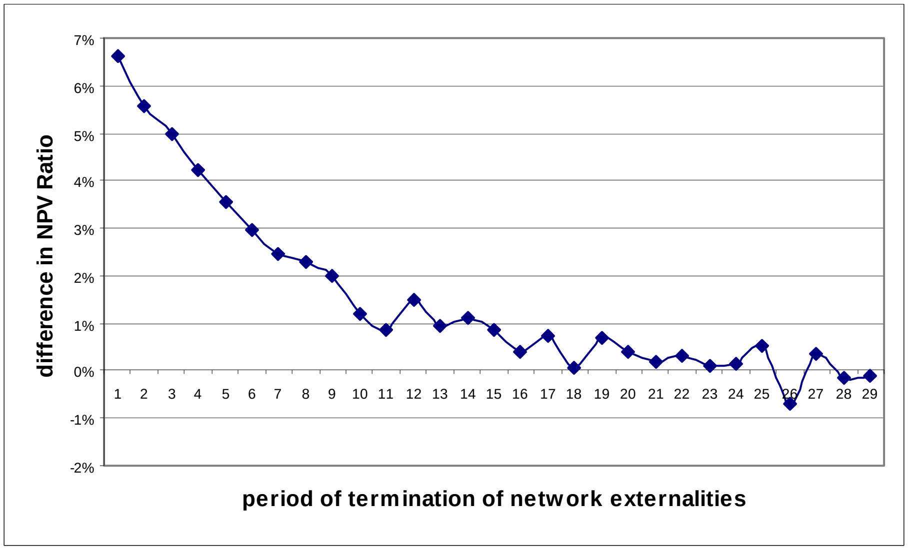
**<u>Effect 2</u>: The larger the variability in the distribution of thresholds in the population, the weaker the effect of network externalities on growth.**

The intuition for this result is not straightforward, the reason being that a greater variance in the threshold causes two effects: Some consumers early in the process will have lower thresholds, and some in the later stages will have higher thresholds. However, this result can be attributed to a phenomenon that we find 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, 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, 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, more consumers at early stages with very low thresholds have a strong effect on the diffusion rate. This asymmetry can be seen in another aspect of Table 1: The strong effect of advertising parameter $a$, compared to internal influence $b$. Since external effects play more dominant roles during the early parts of the diffusion process, and internal effects play more dominant roles after takeoff (Van den Bulte & Stremersch, 2004), this phenomenon may point to the role of the early period in affecting the NPV Ratio.

To better see the asymmetrical effect of the early period, we conducted the following analysis: We ran a cellular automata process wherein the network externalities effect was terminated at various stages of the diffusion process (hence, at some period — labeled "termination period" — all thresholds are set to zero). At first the process was terminated in Period 1, then Period 2, and so forth. For each case, we examined the NPV Ratio. Hence, the difference in the NPV Ratio (between, say, the NPV when the 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 wherein the network externalities effect was terminated. It is clearly shown that network externalities matter much more in the early stages than they do later on. We summarize this result as follows:

> **<u>Effect 3</u>: Network externalities have a stronger effect on profitability early in the product life cycle (PLC) than they do in later periods thereof.**

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

While agent-based models enable us a good understanding of how an individual-level phenomenon becomes a market-level one, one of the challenges of the approach is to tie it to empirical data. One way to do so is to show that the agent-based model's results are consistent with the aggregate-level data that is typically more available for analysis, yet analyzed in a more restricted mode (in our case, for example, a fully connected social network in the spirit of 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 can ask about the possible ways of demonstrating 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 structure is becoming a topic of considerable interest to researchers (see for example Garlaschelli & Loffredo 2008; Toubia, Goldenberg, & Garcia, 2008). Recent studies in this area have demonstrated mathematically that with a homogenous population and large market potential, the 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 the social network structure in 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 a long history of network-based growth processes such as cellular automata (Sarkar, 2000) suggests that they well describe aggregate growth processes. Our aim here is to demonstrate that the results derived by the 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 elaborate on the reason for a difference.

We apply our approach in five cases of new product introduction in the USA that encompass robust externality effects: fax machines, citizen band (CB) radios, cellular phones, DVD players, and CD players.

In order to prompt the aggregate analysis, consider the well-known example of product growth influenced by network effect: the fax machine. The growth of fax in the US from the mid-1960s to the early 1990s was characterized by a slow start and consequently a 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 could be the network effect. 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 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, to incorporate the network effect, we make the 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 the individual thresholds are distributed normally in the population with mean and standard deviation of $h$ and $\sigma$, i.e., with a cumulative distribution function G~N($h$,$\sigma^2$), where $h$ and $\sigma$ 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, since crossing the threshold is a necessary condition for adoption, at that time the market potential is comprised of only those consumers whose thresholds are lower than $N(t)$. Thus, the aggregate adoption function is:

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

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:

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

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 $\sigma$. Note that the Bass model is nested within this modified Bass model of the above equations. In order to achieve the Bass model from Equations (2) and (3), one has to set $h = \sigma = 0$. It follows that $prob(H < x(t)/N) = 1$, 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), using NLS estimation algorithm used herein. We first provide a short description of each innovation, followed by Table 2, which summarizes the estimation results.

**Fax machines:** As mentioned earlier, fax machines were introduced in 1965 in the USA, and took off more than 20 years later. The direct externalities of the fax case are well known and documented, for example, by Rohlfs (2001). The data include annual unit sales in the USA for 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 distinguished from police and military) can use to communicate with any other CB radio operator. The beginning of the CB radio industry is attributed to 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 pick up. The data include annual unit sales in the USA for 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 life of over 49% of the world's population in 211 countries. The data include sales of cellular phones including analog, dual-band, and PCS types (GSM, TDMA, CDMA, etc.) in the USA for 1984 – 2008 (source: eBrain Consumer Electronics Market Research Data).

**DVD players**: DVD players were launched in 1997 into the US market following a delay of at least three years with two competing standards in product introduction. 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 include annual unit sales in the USA for 1997-2008 (source: eBrain Consumer Electronics Market Research Data).

**Compact Disc players:** The CD technology was developed by Phillips in 1979 and introduced in the USA in 1983. The (indirect) externalities of this industry are well documented (see for example Le Nagard-Assayag & Manceau, 2001; Shy, 2001; Gandal, Kende, & Rob, 2000). The data include annual unit sales in the USA for 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:

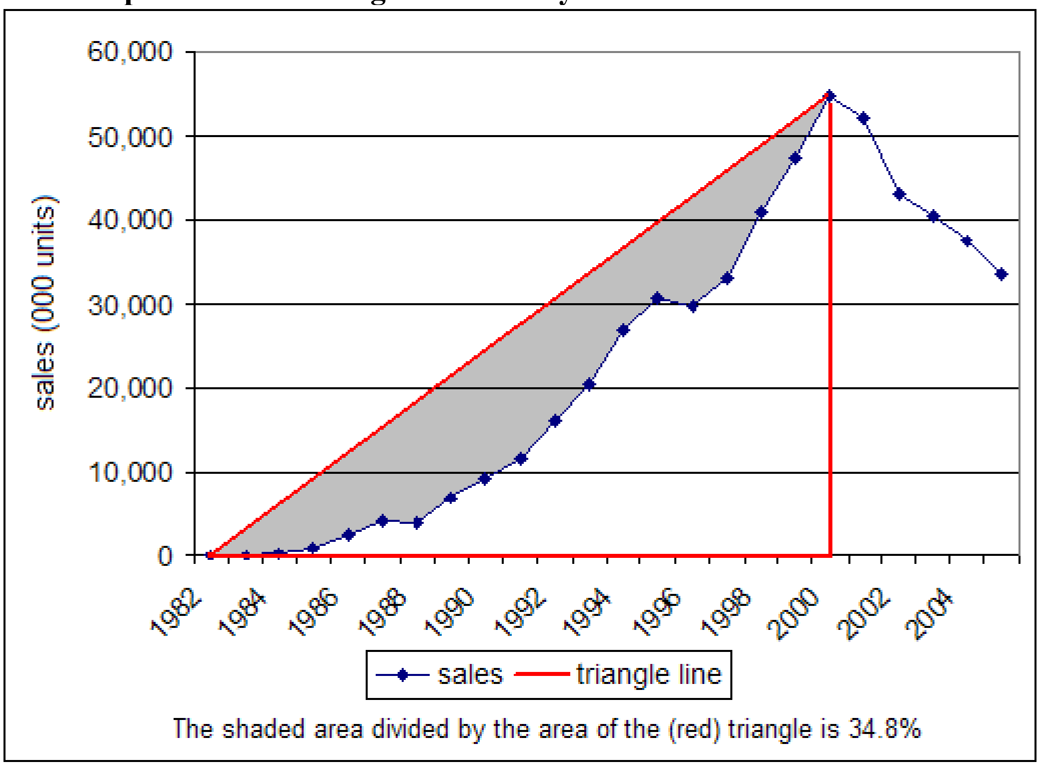
**Heterogeneity of the threshold levels in the relevant population:** Following the above, we expect that heterogeneity in threshold levels will result in a stronger chilling effect. We ran the regressions as described in Equations 2 and 3, and for heterogeneity, we used the variability parameter of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

**Degree of network externality:** 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 on that list. From a network externalities point of view, CB radio is an obvious case of a communication product that should exhibit high network effects. Similar to fax, in the absence of other adopters, the product has very little utility. We thus decided to assess its degree of network externalities as similar to that of fax as assessed by Srinivasan, Lilien, and Rangaswamy (2004).

**The chilling factor:** We computed the NPV ratio 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 the $p$ and $q$ derived by the aggregate analysis, yet 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. Therefore, since the higher the NPV Ratio, the weaker 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 this non-monotonic growth phenomenon to which we point directly 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 the *hockey stick* pattern of growth (Bayus, Kang, & Agarwal, 2007). Consider Figure 4 that shows the growth of CD players in the US, and consider the straight line that connects two points: the time at which the process began (0), and the time of maximum sales, i.e., the year 2000.

**Figure 4 – Computation of the Degree of Hockey-Stick Pattern of 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. In addition, we express this term as a percentage of the area under the line (the red triangle of Figure 4), in perfect analogy 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, for a linear function, the measure will be zero. For the rest of the growth patterns, their 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 fundamental negative effect of network externalities on the growth rate of new products, 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 the effect, consider again the case of the fax. One might wonder what the expected penetrations of fax machines would be if network effects were not present. Regarding fax, imagine a case wherein the government, in the early stage, had allowed all citizens and businesses to conduct all government-related communications by fax. In such a case, the network externalities effect would have decreased substantially. Following a similar method wherein we derived the chilling effect for fax (see above), we examined the expected penetration without externalities.

**Figure 5– Fax penetration with and without network effects**

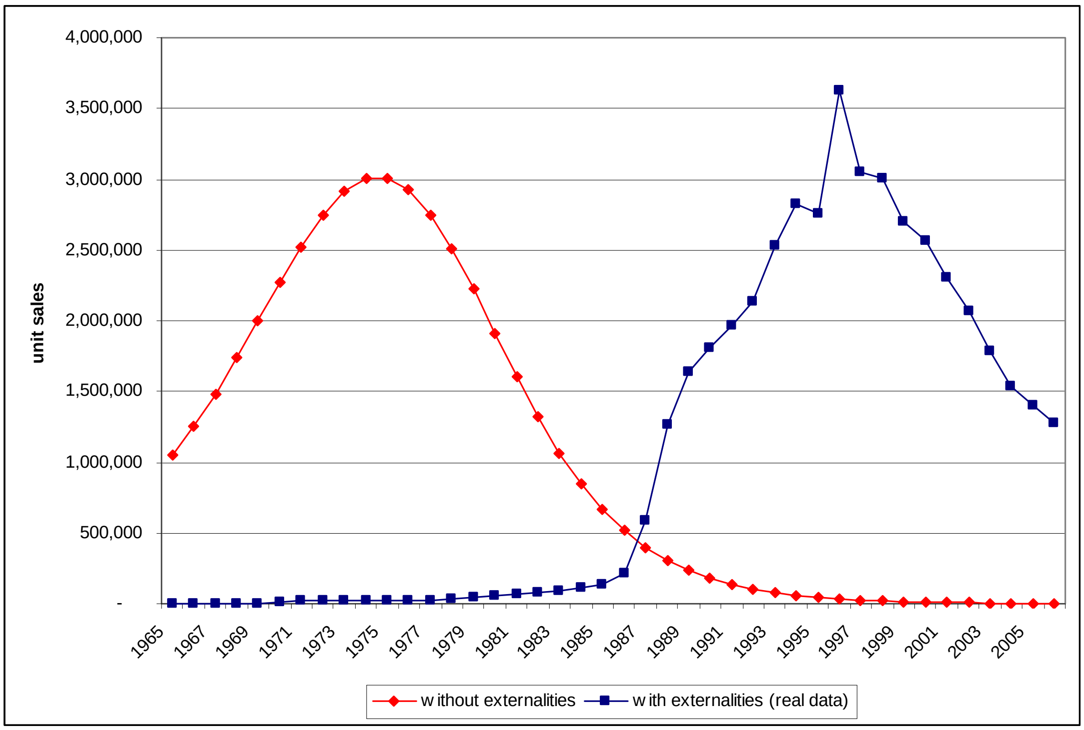



Figure 5 presents the actual growth of fax and its growth in a case wherein no externalities exist (note the similarity to Figure 2, which is an agent-based simulation). In such a case, nearly all penetration would have occurred before 1985, i.e., before the fax's actual takeoff. Using the prices of 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 in the years 1965-1985 is $42 billion (in 1994 values). Of course, other scenarios wherein only part of the externalities effects vanishes and some other dominant factors such as price and quality also halted the adoption process may have been at work. However, these figures demonstrate the magnitude of monetary loss due to network externalities' effect on growth speed in this and other cases.

**The ubiquity of the chilling effect:** Given that later growth may increase in speed due to the bandwagon effect, a possible question arises: Whether we can identify situations wherein later rapid takeoff compensates for an early slow start, and in fact the firm enjoys the overall network effects. We could not identify such cases. First, as reported above, under a wide set of scenarios in the agent-based model environment, we consistently observed a chilling effect on profits. Second, we ran a simulation on the aggregate-level diffusion model wherein we proposed varying diffusion parameters *p* and *q* as well as the threshold distribution, and the results were the same.

Given the above, one might wonder what the reason is for the popular perception of network externalities as driving 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 who join at that stage, the bandwagon effect may be good news in terms of growth rate. However, looking at the entire process from early on, when the entire growth process has to be discounted, the picture is different.

**Competitive considerations and the chilling effect:** Research in network externalities has considered a rate of growth effect in the context of competition, especially for that of competing standards (Farrell & Klemperer, 2006). A basic suggestion is that a pioneer has incentive to boost the speed of growth in order to capture market share that will increase the utility of future and current customers, and possibly render it the eventual standard. Hence firms may want to invest early in R&D and deliberately introduce new incompatible technologies early on (Kristiansen, 1998), or introduce low pricing to deter the entry of a competitor (Fudenberg & Tirole, 2000).

Our results offer two main insights in these regards: First, we demonstrate the financial role of time ***regardless*** of competition, as the chilling effect also occurs in the case of a market monopolist. It points to the motivation of such a monopolist to increase the speed of diffusion, and demonstrates the need to set realistic growth and financial expectations given the 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 a major financial disadvantage. 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 and when planning market strategies in the presence of network externalities.

**Impact of type of products on growth:** An interesting issue to consider relates to the variability in the chilling effect among products. Price is one factor (see appendix): The lower the product's price, the more easily thresholds may be passed, and so the externality factor plays a smaller role. Another source of variability relates to the degree of externalities: As discussed above, one might expect that when externalities play a larger role in customer decision-making, the average threshold required for adoption will increase. A third source of variance may stem from the ***type*** of externalities. 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 case 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, wherein consumers might just have to wait a while until there is enough software to surpass their individual threshold. This will lead to higher thresholds in the case of competing standards. 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, wherein 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 of categories with competing standards (Van den Bulte & Stremersch 2004, 2006).

Of course, if the winning standard is determined early on 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, for example. This might explain the tendency of marketers to offer Internet communications products (whose variable cost is very low) as freeware, or to give them away, and build on other sources of income. For such products, the chilling effect may be rather weak, certainly so with the more costly and older fax and CB radio we looked at 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 better understand this, we conducted a cellular automata exploratory experiment similar to the one reported on above, replacing the global externalities effect with a local one (i.e., if an individual has a 50% threshold, then instead of 50% of the entire social system, it would be 50% of the local eight-cell social network), and commensurately observed a chilling effect (with the exception of no effect with very small local thresholds, as discussed shortly).

The comparison of the global to the local effects is not clear-cut: In some cases, the local had a stronger chilling effect, and in some, 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 in higher percentages thereof, the local setting had a strong effect. The reason is that if the local threshold is low enough, a single adopter in her personal network was enough to surpass it. Since this adopter is also needed for the word-of-mouth contagion effect, the threshold will not play a true chilling role, and the effect is not noticeable. On the other hand, for high means of the threshold distribution, we saw that the requirement of the number of adopters may be more excessive in the personal network. The more precise difference between the local and global externalities effects is an intriguing question. We see such an exploration of the difference as an interesting avenue for future research.

**The distribution of thresholds:** Given the impact of the threshold distribution on sales, growth marketers would naturally be interested in learning how they can assess this distribution. Yet while threshold distribution has played an important role in the collective action literature, there are few empirical demonstrations of how thresholds can be assessed. Empirically, the case of thresholds in the context of a new product growth process is particularly complex due to the interactions with the utility of number of others as a source of personal information. While an exploration of empirical methods to research thresholds is beyond our scope here, we did aim to demonstrate a general direction toward this end.

Intending to directly measure network effect thresholds, we found in two large pre-tests that respondents had difficulty separating these effects. Even when consumers were explicitly told in the context of an adoption of a network good that they already possess positive information about the product, debriefing revealed that the number of others that they demanded in order to adopt a product was related not only to the externality effects, but also to other adopters acting as a cue to product-related information.

In order to separate the network effect from the word-of-mouth effect in a precise way, a two-phase survey was designed. In the first phase, respondents were given a scenario of the penetration of a certain 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 (e.g., videoconferencing ability that demands others with the same kind of phone), and asked again about the number of others needed. The response to Phase I of the questionnaire represents the cue that other adopters supply to the individual in terms of risk reduction, while Phase II includes this risk reduction cue *in addition to* network effects. Hence, the difference between the two phases can serve as a proxy for the need for others due to network externalities on their own. We used these methods presenting undergraduate and graduate students with various scenarios regarding the penetration of network products that included (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 indeed the externalities distribution can be described as truncated bell-shaped. In one study, this distribution was found to be 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, a leftward skewness was evident, and in one, a moderate rightward skewness obtained. Overall, these results support the threshold distribution used in this research. However, we believe that given the importance of threshold distribution presented herein, future empirical research to gain more insights on how to assess the distribution of thresholds and the shapes of the distribution under various market scenarios is greatly anticipated.

## 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 herein 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, either monopolist or a competitive firm, is able to internalize the externality and appropriate the revenue that arises because of the externality (see for example Katz & Shapiro, 1994). The issue of supply constraints has been investigated in a dynamic growth context, yet 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 fax, it is clear that when takeoff finally occurs, the issues of production and distribution will dominate the agenda, unless careful planning was carried out well ahead of time, when demand was relatively flat and growth anemic.

The model we use in the paper that is described in Equation (1) for the agent-based framework and Equations (2) and (3) for the aggregate model, does not specify the 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: additive and multiplicative. Though we opt for the latter rather than the former, behavioral studies that investigate the 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, 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 well complex social phenomena (see for example Sarkar, 2000). In addition, as Watts and Dodds (2007) mention, 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 the basic formulation except for the considerable effects of weak ties, which were not studied in this paper.

Overall, we see this paper as a starting point to 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 to 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 the paper, which is described in Equation (1) for the agent-based framework and Equations (2) and (3) for the 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 wherein individual threshold will depend on the utility from others' presence, 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 level and weight of attributes $j$ respectively for individual $i$, then the individual's utility from the attributes of the product other than the network externality be given by:

$$A_i = \sum_j w_{ij} a_j \tag{A1}$$

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

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

Hence the utility from the product increases with the percentage of adopters, yet is heterogeneous in the population via $\delta_i$. 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:

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

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

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

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

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

The individual parameter $h_i$ is thus the threshold level for consumer $i$ in that the individual will adopt the product if $(x/N) > h_i$. Note that from Equation (A2), for the consumers for which $\delta_i = 0$, utility is just given by $A_i$ and thus they are unaffected by the number of previous adopters. Thus a distribution of network externalities levels $\delta_i$ 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 well reflects the basic premise of our models that relies on the collective action principle: The consumer adopts the 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 the utility was additive in network effects, and thus:

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

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:

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

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 and thus network effects have not yet kicked in. In the multiplicative model, only those with $\delta = 0$ would buy the product at time zero, while in the additive form, there will be consumers with positive weight $w_k > 0$, yet such that 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 of network externalities. Note also that the additive form assumes a linear relationship, while the multiplicative form will exhibit diminishing marginal benefits in the number of adopters if $\delta < 1$ (see also Swan, 2002).

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