IMPACT OF ONLINE WORD-OF-MOUTH ON THE MARKET FOR CONSUMER GOODS – THE INTERPLAY BETWEEN ADOPTION RATE, PRODUCT MARKET LIFE AND MARKET SIZE

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ABSTRACT

Information and communication technologies have given rise to large-scale online word-of-mouth (WOM) referral networks which allow consumers to share information about products. With a larger online referral network, consumers are exposed to higher volume of WOM. Given the increased amount of WOM, consumers could face more intensified social pressures which would alter their adoption behaviors. While prior studies have mainly focused on the volume of WOM on product sales, the second-order effects of those enlarged online networks on consumers' adoption behaviors and the market-level consequences such as product market life and size have not yet been explored. This paper studies (1) the impact of larger WOM networks on consumers' adoption rates, (2) the consequent changes of product market lives and sizes, and (3) how these patterns differentiate across product types. Using 15 years movie data, we first empirically verify that adoption speed could have accelerated around 1998-1999. We attribute this structural shift to the early stages in the acceptance of popular online movie rating websites such as IMDB. Next, we theorize the dynamic impacts of a broader reach of WOM on market structures in terms of market life duration and size via an agent-based simulation model. We further propose four product categories based on different adoption attributes and show that adoption rate, market life and market size evolve differently under different product categories. We conclude with managerial implications of the findings.

Keywords: Online word-of-mouth, online referral network, adoption, product categorization

1. INTRODUCTION

Word-of-mouth (WOM) has long been shown as a driver of product sales (e.g. Richins 1983, Mahajan et al. 1984, Herr et al. 1991). Not only does WOM increase product awareness among potential consumers, but it can also provide information on product quality which assists consumers' purchasing decisions.

With the introduction of Internet-enabled online feedback mechanisms, WOM has moved beyond small close-tie networks (i.e., family, friends, co-workers etc.) to large-scale electronic consumer networks (Avery et al. 1999, Dellarocas 2003a). Whereas a consumer would have acquired WOM just from her family, friends, or local media in an offline environment, the amount of WOM that a consumer is exposed to in an online setting easily exceeds several thousands or tens of thousands. For example, there are over 100,000[1] user ratings and reviews posted for *Star Wars: Episode III – The Revenge of the Sith* (2005) on popular movie review sites such as Yahoo! Movies (http://movies.yahoo.com) or the Internet Movie Database (IMDB; http://www.imdb.com). Indeed the reach, volume and speed of WOM have expanded to an unprecedented scale.

This study is motivated by both theoretical predictions and empirical observations of the impacts from an enlarged online WOM referral network. First, the theory of diffusion and adoption has suggested that consumer's adoption decision will be affected by the amount of inter-personal communication (WOM), which influences them to adopt the product (Bass 1969, Bass 2004). The larger the amount of WOM is, the greater the intensity of the adoption will be. Consequently, the larger scale of online WOM referral network should increase the magnitude of such intensity among consumers and alter the pattern of consumers' adoption behaviors (i.e.

[1] Although consumers may not read every rating or review posted online, this number indicates how much attention a certain product has generated in the market which would influence consumers' decision making process.

adoption speed) as in the offline environment. As a result, the change in adoption pace could potentially shift the balance of market structure (i.e. change the product's market life and size). For example, consumers' adoption speed could become faster due to higher volume of online WOM. In such case, if the increased number of early adopters is just a shift from later adopters (i.e. the overall market size does not increase), we would observe fewer later adopters which shortens the product market life. On the other hand, if the adoption speed decreases under the new circumstance, the market size would be reduced given an unchanged product market life. In other words, during the same time period, there are fewer adopters in general.

Next, given the above theoretical predictions, we use 15 years of box office sales data from the movie industry to empirically verify whether consumers' adoption speed has been changed over time. We find that consumers' movie adoption speeds seem to start accelerating around 1998-1999 when online movie rating sites such as imdb.com have become widely accepted and used. We report our empirical observations in the later section. This finding further suggests that after more and more consumers engaged in online network, their adoption speeds could have been changed over time. Therefore, it is important for both researchers and managers to understand this novel phenomenon which either has happened or will happen in industries where consumers start getting more involved in the online activities.

In addition, researchers have found that consumers' responses to interpersonal communications are different across product categories such as search products versus experience products (Ford et al. 1990, Klein 1998). Thus, the effects from an enlarged WOM network could be different depending on product types. For example, consumers tend to be more skeptical on product information for experience goods than for search goods (Ford et al. 1990). Consequently, they would require larger amount of peers' opinions (WOM) or other sources of information before making adoption decisions for experience goods than for search goods. In other words, product types can reflect how consumers respond differently to social cues about a product. As a result, the impact from the change of WOM network size on consumers' adoption speed and the consequent product life and market size could also be distinct.

The objectives of this paper are to study the impact of the enlarged WOM referral network on individual adoption behaviors and the subsequent market-level effects (product's market life and size). Particularly, we are interested in studying (1) whether and how the expanded reach of the referral network impacts consumers' adoption speed, (2) how the changes in adoption speed affect the product market life and the overall market size, and (3) whether the effects would be different with different product types.

After empirically verifying that consumers' adoption patterns have been possibly altered as a result of the proliferation of online referral networks, we develop a simulation model to theorize the implications of a broader online network under different product types. To capture the distinct effects from the change in WOM network for different product types, we separately study four cases according to consumers' response to social cues under each product type. Based on those four cases, we propose a new taxonomy for product categorization and show that the corresponding impacts on adoption speed, market size, and product life are actually distinguished. For example, for a certain product type such as experience goods, the adoption speed is faster with a larger WOM network which validates our empirical findings. However, the faster adoption speed could lead to a shorter product life as a result of competition of consumers' limited attentions. Moreover, the market size could also be reduced if the negative impact from shorter product life dominates the benefits from faster adoption speed.

Nevertheless, for fashion products, the trends of adoption speed and market size could be opposite. However, product life is also decreased with the increased reach of WOM network.

Our study has important theoretical and practical contributions for both IS and marketing research. To the best of our knowledge, this study is the first within the stream of online WOM research to theorize about *how* IT impacts consumers' adoption behaviors and compare across product types. While prior online WOM research has examined the impact of WOM on product sales (e.g., Chevalier and Mayzlin 2006, Dellarocas 2003b, Dellarocas et al. 2004, Dellarocas and Narayan 2005, Li and Hitt 2004, Liu 2006, Reinstein and Snyder 2005, Zhang and Dellarocas 2006, Zhang et al. 2004), the vast majority of such studies only focused on reproducing offline WOM effects in one specific online context at one point in time. We compare consumers' adoption behaviors over time so as to more directly capture the essence of the impact of IT. We also propose a new computational approach for studying the problem in the same domain. Our simulation model can be easily applied to examine the emerging patterns at the macro-level due to the interactions at the micro-level. From a practical standpoint, our findings can assist companies form better strategies under the new circumstances. Our comparisons across product types provide insights for various companies on how to plan strategies for new product development and introduction. For example, with shorter product market life in general, firms may need to restructure their business processes (i.e., R&D, production, marketing and sales) and reconsider their strategies of introducing a quick minor revision versus a major long-term revision of the current product.

This paper is organized as follows. The next section presents the theoretical background. We then report empirical findings which suggest that adoption rates for motion pictures probably started increasing around 1998-1999 when popular online WOM referral networks began to gain attraction. We follow up with theoretical exploration of the impact of online WOM referral networks, namely the enlarged reach of influence engendered by such networks, via a simulation study. We investigate four cases depending on consumers' different responses to social cues under different product types, and propose four product categories according to those adoption behaviors. Finally, we conclude by discussing implications of the results and suggest future extensions.

2. THEORETICAL BACKGROUND

The theory of diffusion and adoption of new products (Rogers 1995) has been discussed extensively in marketing research (Bass 1969, Mahajan et al. 1990, Sawhney and Eliashberg 1996, Danaher et al. 2001, Dekimpe et al. 2000). The theory suggests that there is a time lag in adopting the new product by different members of a social system. Consumers' adoption decisions would be influenced by the intensity of interactions or inter-personal communications (WOM) around them (Bass 1969, Mahajan et al. 1984, Rogers 1995). The greater the number of individuals who have already adopted, the greater the social pressure to adopt if one hasn't yet done so (Bass 1969).

Subsequent research has used the theory of adoption and innovation diffusion to better forecast sales patterns (e.g., Bass et al. 1994, Dekimpe et al. 2000, Danaher et al. 2001), and to understand the impact of product information, such as WOM, on consumer demand and sales (e.g. Herr et al. 1991, Bowman and Narayandas 2001). It is interesting to note that although *offline* WOM has a rich body of literature (e.g., Richins 1983, Mahajan et al. 1984, Brown and Reingen 1987, Herr et al. 1991, Bowman and Narayandas 2001), *online* WOM generated by those Internet-enabled feedback mechanisms has only recently started generating interest within academia (Basuroy et al. 2003, Dellarocas 2003b, Dellarocas et al. 2004, Li and Hitt 2004, Zhang et al. 2004, Dellarocas and Narayan 2005, Reinstein and Snyder 2005, Chevalier and Mayzlin 2006, Liu 2006, Zhang and Dellarocas 2006). The vast majority of prior literature has focused on understanding the impact of online WOM on the *volume* of consumer demand and sales. For example, Basuroy et al. (2003) and Zhang et al. (2004) investigated the impact of movie reviews on sales and found empirical evidence that movie reviews are significantly associated with box office revenue.

More recently, with the proliferation of online WOM referral networks, researchers have also distinguished the source of product reviews. For example, Reinstein and Snyder (2005) examined the influence of critics' (*expert*) reviews on customer demand and compared the different impacts between positive and negative reviews. They showed that positive expert reviews increase the demand for dramas and narrowly-released movies. On the other hand, Liu (2006) focused on online user (*amateur*) reviews for movies and showed that while the valence of online WOM does not have a significant impact on box office revenue, the volume of online WOM does have a positive impact. In contrast, Zhang and Dellarocas (2006) found a significant impact of online WOM valence where they reported a 1-point increase in the valence on Yahoo! Movies user reviews is associated with an increase in box office revenue in the range of 4-10%. Similarly, Godes and Mayzlin (2004) investigated the role of dispersion and volume of online WOM on future ratings and sales, and showed that dispersion has a lasting indirect association with future ratings while volume does not.

Clearly, a direct impact of information technology in this domain is the unprecedented increase in the volume of WOM brought by online referral networks. However, as discussed earlier, a second-order effect of IT relates to the broader reach of influence enabled by the networked communication technologies. The impact of the increased volume of WOM may have significant effects on consumers' adoption patterns and the market structure for consumer goods. The greater social pressures from the wider reach of the online referral network will impact consumers' adoption behaviors (Bass 1969). The change in adoption speed could in turn affect product market life and size. However, the influences from either an increase or decrease of adoption speed are not deterministic. A faster adoption rate could reduce market size if the market life does not increase accordingly. In other words, the higher number of early adopters is just due to a shift from late adopters rather than new consumers. However, with a non-decreasing market life, the negative influence from a higher adoption rate could be offset and the overall market size could remain constant or even increased. Conversely, a slower adoption rate could also result in a shorter product life along with a smaller overall market size. In short, the ultimate performance of a product in terms of its market size is determined by the dominative effect of either adoption rate or product market life.

In addition, consumers' responses to WOM could vary for different product types (Ford et al. 1990, Klein 1998). For example, Ford et al. (1990) found that consumers gave more creditability to information on search goods than on experience goods. Therefore, consumers would demand more information or higher intensity prior to adopting experience goods. As a result, their adoption speed would vary across product types. In other words, for some product types, they would require higher level of social pressure than others which could result in a slower adoption speed. The subsequent market-level effects (i.e. product life and market size) could also be diversified. In this paper, we are also interested to capture those distinguished patterns. Figure 1 presents the focus of this paper.

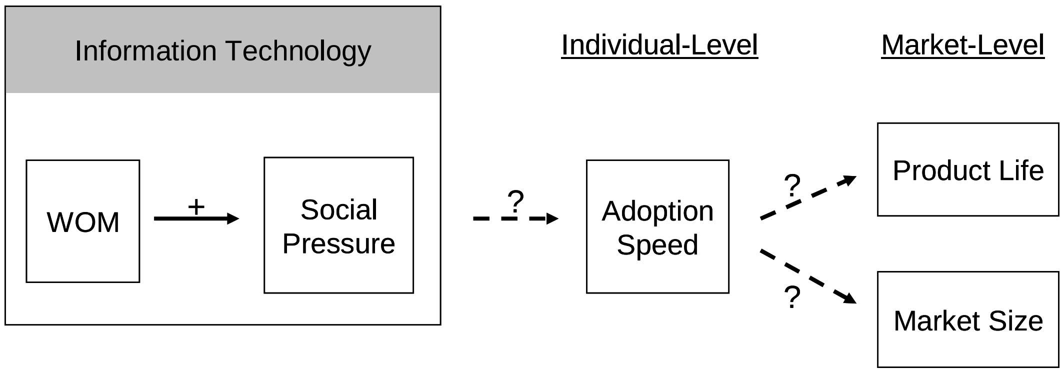

Figure 1. Focus of This Study

Prior research (e.g., Liu 2006) has shown that the volume of online WOM can affect consumers' purchasing decisions (i.e. influence product sales) for some industries such as books and movies. Since online feedback systems have been introduced for years and have attracted thousands of users so far, consumers' adoption behaviors could have already been changed due to the increased social pressures generated online. Thus, before we go in-depth to theorize the dynamic impacts of online WOM referral network, it is worthwhile to first verify whether such empirical evidence exists in the current market. We take a two-step multi-method research process. First, using 15 years of data from 1991 to 2005 from the motion picture industry, we empirically investigate the changes in adoption rates. After ascertaining that adoption rates have indeed changed and that these can be attributable to the wide acceptance and use of online WOM referral network, we further study the dynamics of changes in adoption rates, product market lives and market sizes using a simulation approach. We first present our empirical observations, followed by the simulation analysis.

3. EMPIRICAL OBSERVATIONS

We use the movie industry as the empirical context for our analysis as this industry exhibits several desirable characteristics. First, the movie industry is a popular setting for studying different product adoption related theories (Basuroy et al. 2003, Eliashberg and Shugan 1997, Liu 2006, Reinstein and Snyder 2005, Sawhney and Eliashberg 1996, Zhang et al. 2004). Second, movies have a relatively short life-cycle, which makes it easier to capture the pattern of adoption throughout the whole life time of individual products. Third, freely accessible online movie reviews and weekly box office revenues are used extensively among consumers, and are publicly available.

3.1. Data

Since we intend to measure the change of adoption behavior due to the introduction of online review systems, we select a broad window (i.e., 1991 ~ 2005) that covers the point in time when the Internet-enabled online referral networks became widely used among consumers. We randomly sampled approximately 100 movies for each year from Box Office Mojo (http://www.boxofficemojo.com), a website that tracks box office revenues in a systematic way. A total of 1,375 movies comprise our sample. For each movie, we collected the following data – genre, release date, number of weeks in theater, weekly box office revenue and total box office revenue. Since Action and Comedy are the two most popular genres among consumers, which also represent over 50% of our dataset and have enough data points for each year, we focus the analysis on these two categories[2]. Finally, we also captured average US movie ticket prices for each of the 15 years. The average ticket price was used to estimate the actual weekly number of movie goers by simply dividing the weekly box office revenues by average admission price.[3]

[2] These two categories alone contain 812 movies in our data set.

[3] Note that this procedure over-estimates the actual number of adopters as we cannot distinguish between re-purchases (i.e., a consumer seeing the same movie more than once). However, given that the proportion of repeat customers is usually very small, this over-estimation was deemed to be minimal.

3.2. Measuring Motion Picture Adoption Rates

We use a simplified version of a product diffusion model proposed by Sawhney and Eliashberg (1996) to estimate a *time to adopt* parameter (i.e., adoption rate) for each movie in our dataset.[4] Following Sawhney and Eliashberg (1996), we conceptualize the time-to-adopt a movie to be exponentially distributed with a stationary parameter λ, and therefore the expected time for any individual to be exposed to the information and decide to adopt a new movie is $1/\lambda$. Hence, as λ increases, the expected time for any potential consumer to become an actual adopter is reduced. When λ is extremely large, the expected time to adopt will become approximately zero, which means consumers will adopt the product right after it is introduced. We define a parameter M to be the potential market size – the total number of all potential adopters for a particular product in the market. Each M is assumed to be product-specific and independent of any other product in the market.

Based on the previous assumptions, we can state the following density functions:

PDF: $x(t) = \lambda e^{-\lambda t}$

CDF: $X(t) = 1 - e^{-\lambda t}$

For any given time t, we express the cumulative number of adopters, $M(t)$, to be distributed binomial with parameters M and $X(t)$. In other words, the cumulative number of adopters at time t depends on the total market potential and the probability that a consumer has adopted the product by time t:

$M(t) \sim \text{Binomial}(M, X(t))$

[4] Sawhney and Eliashberg (1996) conceptualized an individual's adoption of a new movie as a two-step process – *time to decide* and *time to act*. The *time to decide* can be influenced by the individual's media habits, WOM, and other communication channels, while the *time to act* is determined by different set of factors such as individual's free time, the availability of the movie in theaters. As the primary focus of our study is on the change in macro-level adoption behaviors, we only consider *time to decide* process which we refer to as *time to adopt* in this paper. Thus, in our simplified model, whenever a consumer decides to adopt the product, she is assumed to be an actual adopter of that product.

Consequently, we may compute the expected value of $M(t)$ and derive the rate of adoption by differentiating the expected value of $M(t)$ with respect to t:

$$E[M(t)] = M \times X(t) = M(1 - e^{-\lambda t})$$

$$\frac{\partial}{\partial t} E[M(t)] = \lambda M e^{-\lambda t}$$

With cumulative box office revenue data, we may estimate the time to adopt parameter λ (adoption rate) for each movie.

3.3. Results and Analysis

In this section, we report the empirical findings of the change in adoption rate and the steps we followed to estimate the adoption rates of movies. After we estimate the adoption rate parameter (λ) and the potential market size (M) for each movie in the dataset, we then fit the estimated λ to a spline regression model to statistically detect a change in adoption rates over time. Spline model[5] is especially suitable for fitting piecewise segments and identifying structural changes within a dataset (Poirier 1973, 1975). Since our purpose is on identifying the changes of adoption rate over time, we use a simple linear spline regression model to capture different patterns of adoption rates during different time periods. Spline functions have been widely used in the medicine, economics and management literatures (e.g., Diewert and Wales 1992, Molinari et al. 2002, Kalyanam and Shively 1998, Greve 1998, 2003). The basic idea behind a linear spline function is quite intuitive. Suppose there is only one knot connecting two segments.

[5] The spline function is a continuous / piecewise device whose pieces can be polynomial segments. The points that join the segments are called *knots*.

Segment1: $\lambda_i = \alpha_0 + \beta_0 Year$, if $Year < Knot$

Segment2: $\lambda_i = \alpha_1 + \beta_1 Year$, if $Year \geq Knot$

Combining the two equations, we formulate the following regression function:

$$\lambda_i = \alpha_2 + \beta_2 Year_{before} + \beta_3 Year_{after} + \varepsilon$$

where,

$$Year_{before} = \begin{cases} Year, & \text{if } Year \leq Knot \\ 0, & \text{otherwise} \end{cases} \text{ and } Year_{after} = \begin{cases} Year, & \text{if } Year > Knot \\ 0, & \text{otherwise} \end{cases}$$

In order to test whether there was a significant change in consumers' adoption behaviors over time, we conduct regression analysis with the estimated adoption rate (λ) as the dependent variable and time (*Year*) as the independent variable. We also include controls for other factors that may significantly impact the adoption rates. First, we include the market size (*MarketSize*), measured as number of tickets sold, since consumers would exhibit different adoption dynamics for more popular movies compared to less popular movies. Second, we include a dummy variable to distinguish between the two genres in our dataset (*ActionDummy*) which takes the value of 1 for action movies and 0 for comedies. Third, we include the motion picture's production budget (*ProductionBudget*) as larger budget movies would typically include larger marketing budgets (e.g., advertising), which would influence consumers' initial level of awareness. Finally, following Basuroy et al. (2003), we control for star power[6] (*StarPower*) by creating a dummy variable that takes the value of 1 if the cast and director include either winners

[6] Liu (2006) and Basuroy et al. (2003) included star power of movies in their analysis of box office revenues. However, they found no significant results with respect to this factor. The negative coefficient that we observe in Model 2 may be due to our choice of genre (action and comedy) since coding academy award winners or nominees as powerful stars would be more appropriate in a genre such as drama. In addition, we also tried defining *starPower* as either the number of movies that actor / actress has been played prior to the focal movie or the average box office revenues his or her movies have generated up to the focal movie. We did not observe any significant results for using these operationalizations.

or nominees for the Academy Award in the categories of Best Actor, Best Actress or Best Director, or 0 otherwise.

Table 1 reports the regression results with 1998 as the turning point[7] (i.e., the knot). Since production budget data was not available for all movies in our sample, we present the results using two separate samples. Sample 1 consists of movies in our dataset for which production budget information was available (N_1 = 454), whereas Sample 2 is the full sample (N_2 = 812).

Table 1. OLS Regression Results (Adoption Rate - λ)

	Sample 1		Sample 2	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	0.3873***	0.4600***	0.3135***	0.3056***
$Year_{before}$ (≤1998)	0.0027	0.0030	0.0141*	0.0122
$Year_{after}$ (>1998)	0.0172***	0.0118**	0.0194***	0.0188***
MarketSize		-0.0079***		-0.0040***
ActionDummy		0.0593*		0.1573***
StarPower		-0.0793***		0.0380
ProductionBudget		0. 0015***		
N	454	454	812	812
F	24.35***	25.57***	48.38***	45.49***
R^2	9.75%	25.55%	10.68%	18.40%
Adj R^2	9.35%	24.55%	10.46%	18.00%
Significance Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$				

The results suggest that consumers' adoption behaviors (in terms of adoption rates) could have changed between 1998 and 1999. For example, the results for Model 2, which includes all control variables, albeit with a reduced sample, suggest that adoption rates were quite stable up until 1998 ($Year_{before}$; β = 0.0030, n.s.) but adoption rates started increasing after 1999 ($Year_{after}$;

[7] Note that a number of models has been estimated by varying the *Knot* year (i.e., from 1992 to 2004). After experimenting with different years for the *Knot*, we found that using 1998 as the *Knot* year produced the best fitting model (in terms of variance explained; R^2).

$\beta = 0.0118$, $p < 0.01$)[8]. The increase in adoption rates is graphically presented in Figure 2, where the overall average adoption rates for the full sample is shown along with fitted linear spline function (i.e., the dashed line).

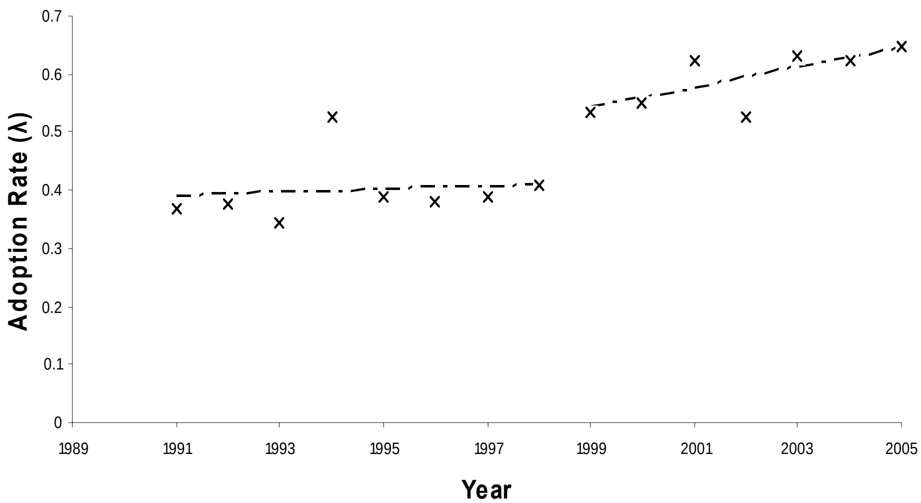

Figure 2. Change in Adoption Rates (λ)

Note: The fitted line represents the estimates from Model 1, which is similar to the figure using results of other models.

The regression coefficients for the control variables were (for the most part) found to be consistent with anticipated signs. For example, action movies seemed to engender faster adoption than comedy movies. In addition, more popular movies with larger market sizes tend to have slower adoption rates (*MarketSize*; $\beta = -0.0079$, $p < 0.001$). Since such movies are shown in theaters for a longer period of time (i.e., longer product market life), this negative impact on adoption rates reflects a more prolonged adoption process compared to a less popular movie which may be removed from showing which would not allow for any additional adoption.

[8] This result is replicated to a large extent in all 4 models where the coefficient for $Year_{before}$ is small and insignificant (or *less* significant, see Model 3) whereas that for $Year_{after}$ is larger and significant.

Moreover, popular movies tend to be sold out, especially during the premiere week. In such cases, even if a consumer decided to go see a movie, she may not be able to do so due to limited supply of showing opportunities (e.g., sold out showing). Consequently, consumers' actual adoption for highly popular movies would tend to be slower given that they would need to wait until the adoption opportunity becomes available. As expected, we also found that the greater the production budget, the faster the adoption (*ProductionBudget*; $\beta = 0.0015$, $p < 0.001$). Movies with greater production budgets enjoy the benefits of greater marketing and advertising, which would help to increase consumers' initial awareness levels. However, we found an unexpected result with respect to star power, which was found to associated with significantly slower adoption speeds (*StarPower*; $\beta = -0.0793$, $p < 0.001$).

Although the results suggest that adoption behaviors have changed over time, it is quite revealing to see that this change may have occurred around 1998-1999, which coincides with the launch of the Internet Movie Database (IMDB), a well respected online WOM referral network. Furthermore, other non-web-based networks (e.g., Usenet Newsgroups) were quite actively used for online WOM in the mid- to late-1990s. Therefore, the results tellingly suggest that consumers' adoption behaviors may be changed as a consequence of online WOM referral networks.[9]

4. SIMULATION STUDY

The previous section presented the empirical observations pertaining to changes in adoption rates potentially due to the diffusion of online WOM referral networks. These findings

[9] We note that it is extremely problematic to pin down a point in time when this shift actually occurred. Like any technology that is voluntarily adopted, online WOM referral networks also undergo an adoption/diffusion process where innovators start adopting and using the system and followers follow suit. Since such online referral networks (e.g., Yahoo! Movies) have recently become popular and widely diffused, we should expect to see continued changes in adoption patterns, at least in the near term.

further motivate us to systematically examine the possible outcomes from the change of WOM network size for various industries. As argued earlier, the main difference between online and offline WOM referral networks is the reach of the network. A broader reach of influence in turn increases the information intensity in adoption process. In this section, we study the dynamic impacts of broader reach of online referral networks on different product adoption attributes depending on the type of the products via a simulation model.

4.1 Modeling Consumer Adoption with Online Referral Networks

We use cellular automata (CA) as the simulation approach to study the impact of enlarged reach of online referral networks on consumers' adoption behaviors (Davis et al. 2007). CA models are appropriate for studying the emergence of macro-level system patterns (e.g., diffusion, propagation, competition etc.) from micro-level interactions of spatially related semi-intelligent agents (Wolfram 2002). CA assumes an ecology of agents (e.g., consumers) who behave according to a few simple rules (i.e., semi-intelligence). These rules relate to how other spatially related agents (i.e., close neighbors or distant strangers) influence one another (Langton 1984). For example, in the management literature, Lomi and Larsen (1996) used CA to investigate macro-level patterns of firm populations (i.e., density, founding and failure rates) that result from the tension between competition and legitimation processes.

In our CA, we represent the population of agents as a two-dimensional $n \times n$ lattice, where each cell represents a consumer. Each consumer, in turn, is represented by a P-dimensional vector that denotes the consumer's interest in P different products of the same product type (e.g., movies). For simplicity, each element p of the consumer's P-dimensional interest vector can have either one of the two values – 1 for active or 0 for inactive. A consumer i is assumed to be interested in, and consequently be engaged in online discussions related to product *j* if the *j*th element of her interest vector, p_{ij}, is equal to 1.

At any given time, the state of a consumer (i.e., the values of a consumer's interest vector) will depend on its own state and the state of a finite number of neighboring consumers. Since consumers are positioned in a two-dimensional space, a consumer's neighbors are those cells that are adjacent to it. The size of the consumer's neighborhood is captured by the parameter k. For example, when $k = 1$, only 8 cells that are in direct contact with the focal cell; when $k = 2$, the number of neighboring cells becomes 24; similarly, when $k = 3$, the number of neighbors becomes 48. In general, the number of neighboring cells equals to $(2k+1)^2 - 1$.

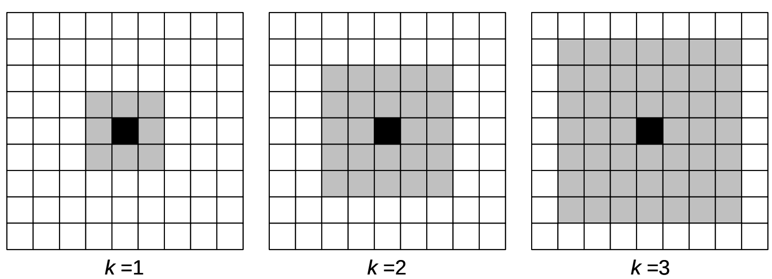

Figure 3. Neighborhood Structures

Note: the focal consumer is represented as the black cell, whereas her neighbors are shaded in gray.

We now specify the simple rules that the consumer agent follows. At any given time, the activity state of a consumer is determined by a density band in the k-neighborhood as defined above. A consumer will become interested in a particular product only if there are enough social pressures (i.e. WOM) around her. We denote l to represent this minimum social pressure (i.e. the lower bound) required for a consumer to become active. In other words, if the number of active neighbors for a particular product j ($j \in m$) is less than l, then the consumer will lose interest in product j and her state becomes inactive (i.e., $p_{ij} = 0$) due to the lack of enough WOM from her neighbors to socially pressure her to become interested in the product. Similarly, if the amount of information is beyond a consumer's maximum tolerance level, she will also lose interest towards that product. Therefore, when the number of active neighbors is greater than the maximum tolerance level (i.e. the upper bound), u, also the consumer's state becomes inactive again. Apparently, these two parameters capture the characteristics of consumers' adoption behaviors related to different product types. For different product types, the minimum social pressure and the maximum tolerance level for a consumer to remain interest of the product should be different. Consequently, the range $(u - l)$ defines the density band and each consumer is increasingly sensitive to the change of her surroundings with the diminishing of this band. Furthermore, due to limitations on cognitive and attention resources, the total number of products that a consumer can be interested in is limited. We represent this limitation by the parameter *attention*. In other words, $\Sigma p_{ij} \leq attention$, for $j = 1,..,m$, for all i. Accordingly, if the number of products for which the number of active neighbors is within the density band (i.e., cause for activation) exceeds *attention*, then the consumer will only be active for those products which have the greatest densities (below u). Finally, a consumer will make the adoption decision (i.e. purchasing the product), if the cumulative number of active periods for that product equals to *adoptPeriods*. The parameter *adoptPeriods* captures the time to adopt a product. Once a product has been adopted by a consumer then it can no longer be activated. In other words, we do not allow for repeat purchases.

The simple behavioral rules above intuitively capture the WOM diffusion process. The minimum social pressure condition (i.e., parameter l) captures a consumer's threshold for triggering interest in a product due to social pressure from her neighbors (Rogers 1995, Bass

1969). The maximum tolerance constraint (i.e., parameter *u*) captures information overcrowding (Jones et al. 2004). In other words, a consumer's loss of interest reflects her coping strategy in the presence of overwhelming information inflow. The range between *l* and *u* defines the interesting information intensity level or social pressure level which attracts consumer's attention on a certain product. Consumer will lose interest if the intensity level goes beyond the range. The neighborhood structure (i.e., parameter *k*) represents the increase in reach due to online referral networks. Without online referral networks, consumers relied on close ties for information about a product; whereas in the presence and use of online referral networks, consumers can gain access to and be influenced by a broader community of neighbors.

4.2 Analysis and Results

Our objective is to study the different impacts of larger network size (i.e. parameter *k*) within different product types (i.e. parameter *l* and *u*) on individual adoption behavior and on market structure. Given the number of parameters, fully exploring the parameter space is beyond the scope of this paper. We fix several parameters to simulate a realistic context and focus on analyzing the impact of different values of *k* (i.e., reach of online referral network) and *l* and *u* (i.e. the adoption attributes associated with different product types). We set the following parameter values as a base case: *attention* = 3 and *adoptPeriods* = 2[10]. The market is assumed to consist of 10,000 potential consumers, which is a 100 x 100 lattice (*n* = 100). We seed the CA

[10] Varying *attention* and *adoptPeriods* could affect the absolute values of adoption rates, market life, and market size. However, the overall trends for these variables are similar. After comparing the adoption curves for different fixed parameter values, we found that *attention* = 3 and *adoptPeriods* = 2 can generate modest adoption speed which allows us to compare across different product types with the increase of *k*.

by randomly activating approximately 40% (i.e. 4000)[11] interest elements in consumers' interest vectors. Furthermore, to mimic new products entering the market, we increment the size of the interest vector after every 10 periods. We use standard Monte Carlo simulation techniques so that more accurate inferences can be made from the simulation results. Particularly, for any set of parameters, we run the simulation 30 times with different random seeds and calculate the mean (and standard deviation) of the dependent variables of interest.

Next, since consumers' adoption behaviors would vary across product types, we separately study different ranges of l and u which represents different adoption attributes under different product categories. We categorize these adoption attributes into four cases – (1) *low* minimum social pressure and *low* maximum tolerance level, (2) *high* minimum social pressure and *low* maximum tolerance level, (3) *low* minimum social pressure and *high* maximum tolerance level, and (4) *high* minimum social pressure and *high* maximum tolerance level. In each case, we keep other parameters constant while varying k from 2 to 10[12], and measure the average product life (i.e., number of periods from introduction to saturation), the resulting average adoption speed[13] (i.e., adoption rate λ), and the resulting average market size (i.e., parameter M in the empirical model) per product. We present the results and discuss the implications for each case in the following section.

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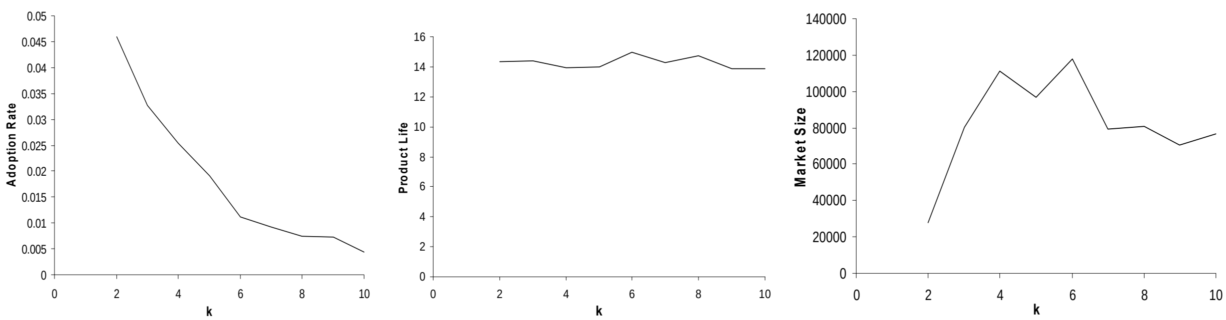
[11] Again, as long as the number of initial seeds is not too small or too large, the results will not vary significantly. By choosing 40% along with the fixed values for *attention* and *adoptPeriods*, the simulation generates reasonable adoption rate for us to study various products in general.

[12] $k = 1$ is too small to produce reasonable results.

[13] We estimate adoption speed (λ) using the model in Sawhney and Eliashberg (1996) outlined in the empirical observations section.

4.2.1 Case (1) – Low l and Low u

Figure 4 presents the results for case (1). We find that when consumers require relatively low social pressure (i.e. low *l*) to become interested in a product and lose interests quickly with the increase of social pressure (i.e. low *u*), their adoption rates will decline in network size. However, the product life is not impacted by such changes in the WOM network reach. Interestingly, the change in market size is not monotonic. It will first increase to achieve an optimal market size with a mid-sized network ($k \approx 6$) and then decrease afterwards.



(a) Adoption Rate (b) Product Life (c) Market Size

Figure 4. Simulation Results of Case (1) – Low *l* (10%) and Low *u* (30%)[14]

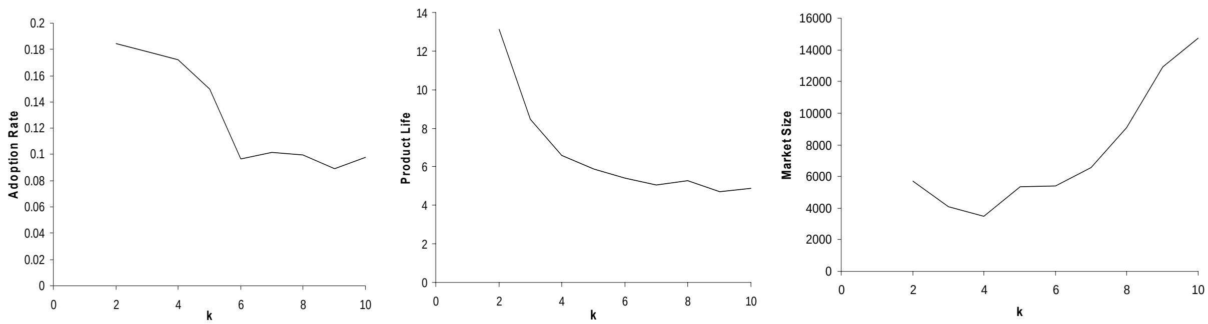
We consider this type of products with both low values of the two parameters (i.e. *u* and *l*) as *exclusive* products such as luxury goods. The value of exclusive products or luxury goods is usually conveyed through its uniqueness or representing consumers' social identity. As a result, for exclusive products, consumers typically do not require much social pressure to generate their interests (i.e. low *l*). In contrast, if they are exposed to too much WOM on the product, they will lose interest quickly since the unique value of that exclusive product decreases (i.e. low *u*). In

[14] We explored the parameter space by varying these two parameters by 5%. We then pick parameter sets which produce valid results for every simulation run. The patterns do not vary much if increasing or decreasing the percentages slightly.

other words, if too many other consumers express interests in the same exclusive products, the attractiveness of that product will be diminished. Intuitively, with a broader network size, consumers could be more easily overloaded or the maximum tolerance level would be reached faster. Therefore, it takes longer periods for those potential buyers to make the final decisions (i.e. the adoption speed decreases). However, its product life would not be affected by such slower decision making process. As a manufacturer or retailer, the delay in adoption decision process does not hurt the market size at the initial stage of the increasing in network size. In fact, companies can expect more profits with the larger reach of network. Unfortunately, the decreasing in adoption speed starts hurt the market when the size of the network becomes sufficiently large. As a result, companies should start to develop certain strategies to control the size of the online community for their targeting consumers so as to maintain the optimal market size level.

4.2.2 Case (2) – High l and Low u

In case (2), we investigate in the adoption behavior which demand relatively high minimum social pressure and low maximum tolerance level. Different from case (1), consumers will not become interested in the product if there are just a few discussions (i.e. high l). However, again, they will lose interest quickly after the social pressure reaches a relatively low level (i.e. low u). As shown in Figure 5, similar to case (1), adoption rate is decreasing with a larger network size at first. Interestingly, there seems existing a threshold of network size, beyond which the adoption rate stops decreasing (i.e. $k > 6$) and becomes stable. Along with the decline in adoption rate, the product life curve is also decreasing significantly from a small sized network towards a mid-sized network and becomes flatter after it reaches a large WOM network size. Surprisingly, the combining effects from adoption rate and product life produce an exiting curve for market size. Although it slightly decreases at the beginning, the market size soon increases almost exponentially afterwards.



(a) Adoption Rate (b) Product Life (c) Market Size

Figure 5. Simulation Results of Case (2) – High *l* (30%) and Low *u* (50%)

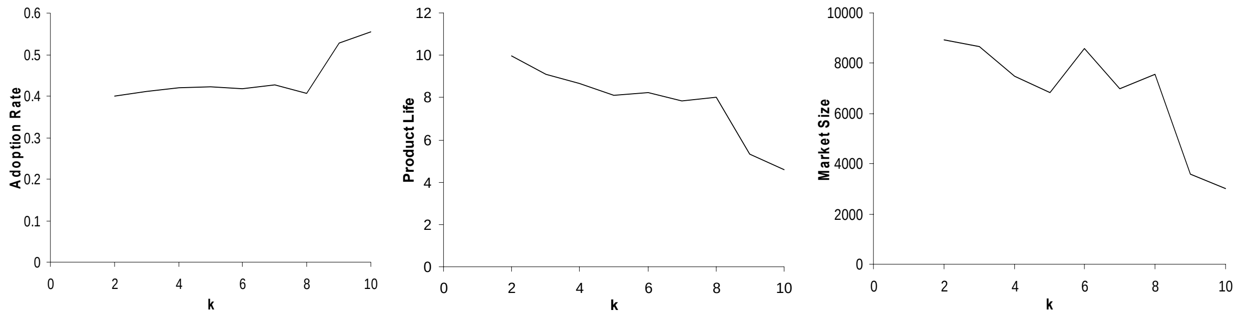
Based on the characteristics of adoption behavior, we called this product type as *trendy* products such as fashion goods. Consumers in this category share some attribute as in the exclusive product category. They also utilize the product to express their self-images (Miller et al. 1993), and thus do not expect the product to become too popular in the market. However, a product has to attract quite a few attentions in the market to be considered as a successful trendy product. Therefore, products in this category require a substantial amount of WOM so as to attract a new customer, whereas the discussions cannot be overwhelming so that consumers will lose their interests. For example, consumers may start becoming interested in a certain style of handbag if quite a few of their peers or online users are discussing about the bag. However, if there appear too many potential buyers they will hesitate in making the purchase since that handbag could become very common on the street which reduces its value. Companies engaged in such industries should be careful to deal with both positive and negative consequences brought by the larger reach of WOM networks. On one hand, the large network does increase the potential market size of the product. On the other hand, at the same time, it shortens the product life which creates a challenge for the product development department to introduce new products in a much tighter time constraint.

4.2.3 Case (3) – Low l and High u

In this category, consumers do not need much information before adopting the product whereas they can tolerate high level of information intensity. In other words, their interests of the product are not sensitive to the amount of WOM in their neighborhood. Consumers could be interested in one product no matter how many other consumers are also interested in the same product. We attribute this product type to be *search* goods of *commodity* products such as pens or screwers. Since consumers typically do not have to require much information for search goods before they make a purchase, we did not observe substantial WOM diffusion in our model. In the same vein, the consequent market-level variables, product life and market size, will most likely not be affected with the increases in the neighborhood size.

4.2.4 Case (4) – High l and High u

Consumers in this category require sufficient WOM to attract their attentions (i.e. need relatively high minimum social pressure). However, different from case (1) and (2), their maximum tolerance level is also high which suggests that consumers do not value the uniqueness of the product as much as in the first two cases. We present the results in Figure 6. Opposite to what we find in the first two cases, the adoption rate increases after the network size k becomes large ($k > 8$). However, the product life is shortened. It seems that the negative impact from a shorter product life outweighs the benefit from a faster adoption rate. As a result, the market size shrinks substantially once the network size surpasses the critical point (i.e. $k > 8$).



(a) Adoption Rate (b) Product Life (c) Market Size

Figure 6. Simulation Results of Case (4) – High *l* (35%) and High *u* (85%)

We propose this case to represent the *experience* goods of *commodity* products such as movies or books. Since consumers have to acquire adequate information for experience goods before purchasing, the minimum social pressure for this product type should be relatively high. However, the attributes of commodity products determine that the consumers care less about how common the products will be in the market. The high value of *u* captures this characteristic. Since consumer's adoption behavior in this category is highly dependent on social pressure, the faster the WOM diffuses, the higher the adoption rate will be. This simulation result also validates our empirical observations discussed in the previous section. Companies developing such products should be cautious of their consumers getting more involved in online WOM network. Although faster adoption speed seems to benefit firms initially, the decrease in product life and market size could potentially hurt the overall profits. Moreover, with the shortened product life, companies have to adjust their product development and introduction strategies accordingly to be able to meet the market demands.

4.3 Summary

We propose a new taxonomy for product categorizations depending on consumers' adoption attributes. With the increasing popularity of using online feedback mechanism to assist consumers' purchasing decisions, consumers' adoption behaviors have been altered gradually in the recent years. Our study outlines the corresponding adoption rate changes according to different adoption attributes and predicts the resulting impacts on product life and market size. We find that in most of the cases (case (2) and case (4)), despite the direction of the changes in adoption rate, product life will be most likely shortened due to faster WOM diffusion. This situation presents interesting novel challenges to managers in firms producing and marketing consumer goods. Firms may need to prematurely discontinue product lines or may be required to introduce new products at a faster rate in order to maintain a healthy revenue stream. This also puts more pressure on firms' R&D efforts as firms would need to develop new or successive products within a much tighter time frame. Such changes will have significant impacts for management practice and research. We summarize the mapping of product types with consumers' adoption attributes and the changing directions for the variables of interest in Table 2.

Table 2. Summary of Simulation Results

l (Minimum Social Pressure)		*u* (Maximum Tolerance Level) Low	High
		Exclusive Product	**Commodity Product** ***Search Goods***
Low	Adoption Rate	-	
	Product Life	No change	
	Market Size	-	No WOM Diffusion
		Trendy Product	***Experience Goods***
High	Adoption Rate	-	+
	Product Life	-	-
	Market Size	+	-

Note: -, decreasing; +, increasing.

5. CONCLUSION

This study investigated the impact of information technology (IT) on the structural implications for markets of consumer goods. More specifically, we examine the impacts of an enlarged reach of influence brought about by online WOM networks on adoption rates and its subsequent impacts on products' market life durations and sizes. Our empirical observations of weekly box office revenues suggest that the speed of adoption (i.e., adoption rate) has accelerated starting around 1998-1999. We attribute this shift in adoption rates to the beginning of the diffusion of online reviewing websites such as IMDB. The use of online WOM referral networks opens consumers to a broader network of others that may influence one's adoption decisions. We conjecture that the enlarged reach of influence would have resulted in greater information intensity (i.e. social pressure) for consumers to adopt, which in turn changes the overall adoption and diffusion process. Although it has been shown that increases in WOM volume is typically associated with increases in product sales for some industries such as books and movies (e.g. Chevalier and Mayzlin 2006, Liu 2006, Zhang and Dellarocas 2006), the dynamic implications of the larger online network of WOM is not entirely clear.

Our simulation results shed initial insights into this phenomenon. Using a cellular automata framework, we develop a simple simulation model of consumer adoption with online referral networks. Our simulation results show that depending on consumers' adoption attributes regarding different product types, the impacts from the increased reach of WOM network could be different. We propose four product categories based on adoption behaviors, and discuss managerial implications for companies to better prepare for the new challenges created by this novel phenomenon. For example, companies can manipulate the consumers' WOM network size so as to obtain the optimal market size. For exclusive products, companies can develop certain strategies to maintain a moderate network size for their market segments. Setting boundaries such as charging club fees or membership fees to prevent an over-sized network could be one effective approach. Differently, companies engaged in trendy industries should encourage the growth of online networks. Offering online discussion spaces or affiliating with popular websites would be a promising strategy. In addition, under the new circumstance, companies should also be cautious in interpreting the sales figures. For example, for experience goods, although adoption rates are increased under larger WOM network, the products' market life and size could be reduced. In other words, product sales may exhibit desirable sales pattern initially. The benefits could be offset by the reduced overall market life and size which make the product become unprofitable much sooner than anticipated. Conversely, for trendy products, although the adoption speed could become slower, the overall market size may increase exponentially with the broader influence of online WOM.

This study is not without limitations. First, the empirical data may not accurately pin-point the exact moment in time when adoption rates have shifted and further any shifts detected may be due to a host of factors other than online WOM networks. However, while we cannot formally prove that the reason for the observed shift in adoption rates is the diffusion of online WOM networks, the empirical results are nevertheless suggestive. Second, as with any research study that uses simulations as the analytical tool, this research made some simplifying assumptions about consumers, products and markets in order for the simulation to be tractable. For example, consumers were modeled as semi-intelligent. Furthermore, all consumers and products were modeled as being homogeneous in each simulation run. However, despite the simplifying assumption, we were able to reproduce the general mechanism that underlies the WOM, adoption and diffusion processes, which were in turn used to explore the implications of increasing reach of influence of online WOM networks. By closely following the prescribed process for theory building using simulations (Davis et al. 2007), we feel that the insights generated are noteworthy despite the inherent limitations of simulations. In a similar vein, simulation methods are not appropriate for hypothesis testing. Rather, it is a useful vehicle for theoretical exploration. Consequently, the insights uncovered in this study should be empirically tested in order to provide stronger support for our theoretical arguments.

Despite the above limitations, this paper has important theoretical, methodological and practical implications. In terms of theoretical contribution, this study is the first to go beyond investigating the immediate impact of online WOM networks to theorize about the impacts on market structure for consumer goods (i.e., market life and market size of products). In addition, we separately study the different effects within different product types, and propose four product categories based on adoption attributes. Our results provide theoretical predictions for the impacts across categories. In terms of practical implications, this study suggests that early market success or failure in terms of initial sales may not be good predictors of long term sustained market performance. If increases in adoption rates are not accompanied with a substantial increase in market size, a product may be shorter lived. On the other hand, the slower adoption speed may actually produce a larger market size. We also offer precautions and early warnings to managers with respect to various managerial challenges that would need to be carefully handled if the market structures were to shift to such new dynamics. Finally, in terms of methodological contributions, our study provides an approach (i.e., simulations using the cellular automata framework) for studying and exploring such research questions related to macro-level structural changes that result from micro-level interactions. We believe that the cellular automata model presented in this paper offers a rigorous approach that can be readily applied for future extensions. For example, by varying how new products are introduced in the market (e.g., sequential vs. concurrent; or close to one another or further from one another in time etc.), or how the consumer network is initialized (e.g., in terms of size or location), it should be straightforward to explore the consequences relative competition between products or marketing efforts in introducing and promoting products.

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