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Hyping diffusion: all adopters are not equal

Abstract

Often new products, especially high technology products, exhibit a distinct spike in sells at the beginning before settling into a smooth parabolic shape. Apart from the pronounced early spike, sales of new products follow the traditional pattern described by traditional equation based diffusion of innovation models. This paper attributes these spikes to indirect network effects. To explain indirect network effects in diffusion models, the authors extend the Bass (1969) framework by proposing two categories of adopters – thus a third group of customers – and by doing so improves prediction. The first category of adopters – traditional innovators and imitators – see enough value in the new product and adopt it as they become aware of it, through either mass media or word of mouth. These adopters give rise to the initial spike often observed in diffusion of innovation models. The second category of adopters assign a value to products, depending upon the indirect network externality associated with each product. They adopt products only when the value exceeds a threshold.

Keywords: diffusion, innovations, new product, equation-based modeling, agent-based modeling, network externalities, saddle, social network.

Introduction

Being the 'eyes and ears' of organizations, marketers are often assigned the task of forecasting the demand for new products. This places us in a precarious position. Not only do we have to set quantities, but we also have to know how to set the marketing mix throughout the product life cycle. Since most of us are not clairvoyants, we use forecasting tools to aid us in our decision-making. One such tool is diffusion of innovation models. In this paper, we will broadly discuss diffusion of innovation models and discuss our refinement to equation based diffusion of innovation models.

The theory of the diffusion of innovations looks at how a population assimilates new ideas, goods or services. The diffusion process describes how an idea, good or service spreads through a social system (Rogers, 2003). The adoption process details how individuals accept an innovation, from the time of first noticing the innovation until final adoption. Diffusion of innovation models are appealing because these models are instrumental in the accurate prediction of product adoptions. Broadly there are two types of approaches used to develop diffusion of innovation models – equation-based and agent-based approach.

Equation-based diffusion of innovation models mainly consist of nonlinear differential equations. These nonlinear differential equation models can encompass a wide range of feedback effects, but typically aggregate agents into a relatively small number of states (compartments). In equation-based diffusion models the typical states consist of how the actors were informed and whether they are adopters or non-adopters (Mahajan et al., 2000). Within each compartment, people are assumed to be homogeneous and well mixed; likewise the change from one state to another is modeled as the expected value of the transition.

Agent-based modeling (ABM) consists of a computational method of studying social agents as evolving systems of autonomous interacting entities. As such, ABM allows for the study of social interactions in the form of a complex adaptive system. In contrast to equation based models, ABM models can readily accommodate the interaction of heterogeneous social network structures. Yet, just like equation based models, ABM models can be deterministic or stochastic and can account for feedback effects. Although versatile, ABM models have two conceptual and computational costs (Rahmandad and Sterman, 2008). First, the ability of ABM models to deal with complex interactions results in significantly higher computational requirements. Second, ABM models incorporate a much greater level of detail, this level of detail places a cognitive burden on understanding model behavior. It becomes increasingly difficult to understand the behavior of a model in relation to its structure as model complexity grows. These conceptual and computational burdens constrain the ability to conduct sensitivity analysis.

The parameters in equation-based diffusion of innovation models have appealing intuitive behavioral interpretations. The Bass (1969) model is the most widely accepted diffusion of innovation model (Lilien, Kotler & Moorthy, 1992). Bass (1969) integrated contagion models from epidemiology into the framework devised by Rogers (1962); thus creating a new method of forecasting product adoption using the diffusion process. There are two basic assumptions under the Bass (1969) model: mass media communication and interpersonal communication are the main influencers of product adoption. Consistent with these assumptions, there are two types of adopters: innovators and imitators. Mass communication has the greatest influence on innovators, while interpersonal communication has the greatest influence on imitators.

Under the basic diffusion of innovation framework, the adoption of a product is independent of all other innovations. Yet, we know that complimentary products often influence the adoption of the primary products. Some products are contingent on other products, for example prerecorded videos and video players. Without DVD recorders/players the sale and rental of DVDs would not occur. The DVD recorders/players would be the primary product, while the prerecorded DVDs would be the dependant product. In cases where one innovation is contingent upon another innovation, research to date considers the primary product to greatly influence the market potential of the dependant product (Peterson and Mahajan, 1978; Bayus, 1987). While no researcher suggests that dependant or complementary products do not play a role in the diffusion of the primary product, it is not clear what effects these complementary products have on the diffusion of the primary product. Yet, we intuitively understand that the availability of prerecorded media (i.e., prerecorded music or DVDs) influences the sale of media play-back devices (i.e., portable listening devices or DVD players) (Stremersch et al., 2007). Clearly, the lack of network externalities can reduce the number of future sales (Goldenberg, Libai and Muller, 2010).

The public and marketers have known for sometime that the early introduction of products requires exuberant promotion. Often marketers spend an inordinate amount of time on publicity and public relations to facilitate the successful launch of products. Many people consider the early claims about the abilities of a new product or service to be overblown hype. These people prefer to wait for an innovation to be around for some time before settling to adopt the product. The Gartner Group, a provider of research and analysis on the global information technology industry, describes this process through a "technology hype curve". Indeed, the literature (Goldenberg, Libai and Muller, 2002) supports the fundamental observations of the Gartner Group. Goldenberg, Libai and Muller (2002) observe that between one-third and one-half of the sales of innovative products in the consumer electronics industry follow a similar pattern: excluding random fluctuations – there is an initial peak, then a trough, followed by a higher peak and finally declining sales. Goldenberg, Libai and Muller (2002) term this sales pattern as a saddle. In the original Bass (1969) paper there was a saddle present in the diffusion of black and white television sets.

Goldenberg, Libai and Muller (2002) arrive at this distinct saddle pattern through empirical analysis and by modeling sales utilizing cellular automata. Cellular automata modeling, which is a form of ABM, consist of simulating the interaction among members of a local population. Accordingly, the saddle pattern results in the merging of two distinct customer markets: early markets and main markets. Until now, researchers have mainly lumped later adopters into the category of imitators. Although ABM methods – such as cellular automata – do an excellent job of demonstrating that dual markets exist, it only offers variation among social clusters as the reason behind the existence of separate markets. Here, we explain that in some cases multiple market variation may be the result of complementary dependant products, not necessarily independent social actors. When complementary dependant products occur, some sets of adopters will require high levels of complementary products prior to adoption, while other sets of adopters require low levels of complementary products or externalities. Additionally, some products require network externalities. For example, cellular phones are useless without cell phone towers; however, handheld calculators require no such infrastructure.

This line of inquiry potentially gives us a more nuanced understanding of the diffusion process. Having a more nuanced understanding of the diffusion process allows marketers greater latitude in setting the marketing mix. To add a greater degree of nuance, we refine diffusion of innovation models by examining the role that secondary complementary products (externalities or network externalities) have on the adoption of innovation. Specifically, we examine the effect of network externalities on the adoption of the primary product. Instead of just considering a single category of adopter, we consider two categories of adopter. The first set of adopters being the traditional innovator/imitator. The second category of adopter will only consider a product or technology when sufficient infrastructures or externalities are in place.

1. Background

Rogers (2003) considered the adoption of innovation as being a system populated by two types of individuals, innovators and imitators. Under this framework, adoption of innovations is a social enterprise reliant upon interpersonal influence, or opinion leadership, activating diffusion networks. Accordingly, innovators communicated their experiences to early adopters; likewise both innovators and early adopters communicated their experiences to later adopters. The later adopters are either encouraged or discouraged from adopting a product based on the experiences of the early adopters. The impact of this influence varies from person to person. This opinion leadership is product-area specific; often because leaders have more information than followers do.

Bass (1969) distilled Roger's framework into an equation utilizing a hazard function. In this equation, the coefficient of external influence multiplied by the difference between the market potential and the cumulative number of adopters describes innovators. The coefficient of internal influence multiplied by the ratio of cumulative adopters and market potential then multiplied by the difference between the market potential and the cumulative number of adopters describes imitators. The combination of the innovators and imitators gives the total number of adopters. Likewise, the difference between the market potential and the cumulative number of adopters gives the number of potential adopters. Therefore, in the Bass diffusion of innovation model, both the effects of internal and external sources of information are a function of the number of potential adopters.

Tanny and Derzko (1988) contend that the Bass model fails to capture the communication between innovators and imitators, as stated in Rogers' model. Rather, the Bass model actually reflects two distinct groups – potential innovators and potential imitators. The potential innovators are only influenced by mass media, while the imitators can be influenced by either mass media or word of mouth. Mahajan, Muller, and Bass (1990) address this by renaming adopters as those influenced by external communication, and those influenced by external and internal communication channels.

Many scholars have questioned that the underlying assumption of the Bass diffusion model may not be sufficiently robust. Mahajan, Muller and Bass (1990) claim that these simplifying assumptions "provide a parsimonious analytical representation of the diffusion process." Yet, these authors have (Mahajan, Muller, and Bass, 1990) acknowledged that there are many assumptions that warrant attention. Specifically, we address two of these assumptions. First, the market potential of new products remains constant over time. Second, in the Bass model, product and market characteristics do not influence diffusion patterns.

The literature does consider how certain market externalities influence equation based diffusion models. Mahajan and Peterson (1978), Sharif and Ramanthan (1981), Kalish (1985), and Horsky (1990) examine dynamic market potentials. Jones and Ritz (1987) and Lackman (1978), respectively, looked at the influence of growth in the number of retailers, and the profitability of the product on the market potential. Bayus (1987) considered complementary products. However, none of the literature examines how externalities fundamentally influence the consideration to adopt the primary innovation in equation based diffusion models. Further, concerning equation-based diffusion models, the literature fails to consider whether individuals exist on a continuum rather than being purely imitator or purely innovators.

In the standard diffusion of innovation model, product and market characteristics do not influence diffusion patterns. Rogers (2003) and Tornatzky and Klein (1982) suggest that empirical studies show the contrary; diffusion patterns are influenced by product and market characteristics. Kalish and Lilien (1986) assessed the impact of changing consumer perceptions of product characteristics as the product is adopted over time. Gatignon, Eliashberg and Robertson (1989) considered the impact that market characteristics have on the diffusion of a product. Most of this work has led to inconclusive results; therefore, more research is needed in this area.

Each refinement to the Bass model purports to address a particular shortcoming. For example, Bayus (1987) conducted a study examining the diffusion dependence between compact disc hardware and software. A product's diffusion is contingent on the primary product. Here, the primary product would be compact disc players, and the contingent product would be compact disc software. Not all products are contingent on another product. Although the refined model produces superior forecast, refining the basic diffusion model to handle contingent products has limited use. Therefore, any refinement that incorporates complementary products should collapse into the basic model when complements are unnecessary.

Most forms of diffusion models describe adoption as a smooth parabolic curve. Models based on cellular automata (Goldenberg, Libai and Muller, 2002), along with the Gartner technology hype curve, display a distinct bimodal pattern. Models constructed utilizing cellular automata and the hype curves are consistent with diffusion theory; there are early adopters – primarily influenced by external sources of information, and late adopters – primarily influenced by observation of earlier adoption. Both cellular automata and the hype curve consider the existence of two distinct early and late markets. Cellular automata models consider the early markets and late markets as being comprised of distinct social groups instead of fully connected and homogenous social networks (Peres, Muller and Mahajan, 2010). While, the hype curve framework considers early adopters as being influenced by unsubstantiated claims of a particular innovation. These unsubstantiated claims are the initial 'hype'.

Under the hype curve framework, the number of adopters grows at a rapid rate as the innovation becomes known. The claims may be unsubstantiated given the newness of an innovation, but they are nonetheless attractive (Gartner Group, 2002). Once people observe or sense that the innovation cannot perform to the level of its claims, the number of adopters reaches a peak, eventually falling-off as potential users realize that the innovation does not meet all of the original claims. The level of adoption continues to trail-off, until either the innovation matches the initial performance claims or externalities are available to make the initial claims possible. In this way, the hype curve framework considers the market potential of new products as variant over time, and that product and market characteristics influence diffusion patterns. The hype curve also introduces a new type of adopter, one that considers the practical aspect of an innovation. For example, when faced with deciding to adopt a new type of personal computer or smart phone, this practical adopter would wait for the availability of adequate software before purchasing any one of these devices.

Our refinement to the diffusion of innovation model considers not only the type of adopter but category of adopter, as well. The first category of adopters see enough value in the new product and adopt it as they become aware of it, through either mass media or word of mouth. The first category of adopters gives rise to the initial sales spike. The second category of adopters assign a value to products, depending upon the indirect network externality associated with each product. This second category of adopters adopts products only when the value exceeds a threshold, which varies across the adopters. The second category of adopters, the inductors, uses inductive logic concerning the usefulness of an innovation. The inductors are consistent with the hype curve framework-inductors are neither innovators nor imitators. Further, consistent with cellular automata, inductors could be considered as a distinct group. Inductors, as a group, would be similar to innovators-in the sense that external information and introspection influences this category of adopter more than immediate social contacts; however, they may have first learned of or observed a particular product or technology through social contact. In the following section, we will incorporate this new category of adopter into a diffusion of innovation model.

2. Model

Like Bass (1969), we assume that the probability of an initial purchase being made at time T is a linear function of the number of previous buyers and the propensity to purchase absent of other buyers. Given that $\overline{Q}$ is the total number of purchases or adopters; p is a constant representing number of innovators-purchasers that do not require other purchasers; q is a constant representing the number of purchasers depending upon the number of previous purchases, and $Y(T)$ represents the number of previous buyers. The likelihood of purchase at time T given that no purchase has yet been made is given by the following expression

$$\frac{f(T)}{[1-F(T)]} = P(T) = p + \frac{q}{\overline{Q}} Y(T). \tag{1}$$

Instead of two types of buyers, we will consider a third buyer, a buyer who would be an innovator, but requires externalities before making a purchase. In many cases, a firm or third parties provide externalities that will enhance the use of a product. For example, color televisions proved to be no advantage when programs were recorded in Black and White; likewise, video games consoles, computers and smart phones all require software. Third parties will often hesitate producing the externalities necessary to use the primary product until a sufficient market exists. Consistent with economic thought, the supply of external products is proportional to demand. The only information that suppliers have concerning potential demand would be current sales of the primary product. This means that the inductors are indirectly influenced by prior demand, since they will wait until third parties create sufficient levels of products or infrastructure to facilitate using the primary product. With $Y(T)$ being the number of purchasers and r being a constant proportional to the supply of externalities, the supply of externalities corresponds to $rY(T)$. Additionally, q_e reflects the number of purchasers requiring externalities. The conversion ratio for adopters requiring externalities would be $rY(T)\, q_e$, the model now becomes:

$$\frac{f(T)}{[1-F(T)]} = P(T) = p + \frac{(q)}{\overline{Q}} Y(T) + \frac{\rho Y(T) q_e Y(T)}{\overline{Q}}. \tag{2}$$

This equation reduces to:

$$P(T) = p + (q)F(T) + \rho q_e \overline{Q}[F(T)]^2, \tag{3}$$

where $f(T)$ is the likelihood of purchase at T and

$$F(T) = \int_0^T f(t)\,dt. \tag{4}$$

With $f(T)$ being the likelihood of purchase at time T and $\overline{Q}$ is the total number of purchasers over the period of the density function

$$Y(T) = \int_0^T S(t)dt = \overline{Q}\int_0^T f(t)dt = \overline{Q}F(t). \tag{5}$$

The sales at period T is given by:

$$S(T)=\overline{Q}f(T)=P(T)[\overline{Q}-Y(T)]. \tag{6}$$

The portion of sales attributable to innovation and imitation extends over the entire range from $t = 0$ to $t = T$; however, with the portion of sales attributable to inductors, the network externalities must reach a critical mass. Network externalities can occur at any time either before after or during the launch of an innovation. In cases where the network externalities pre exist or are introduced simultaneously with the innovation, the portion of sales attributable to network externalities being in place will start at time $t = 0$. However, in cases where the network externalities reaching a critical mass after the launch of the innovation, the portion of sales attributable to network externalities will start at some time t. Network externalities reaching a critical mass after the initial launch of an innovation is consistent with an initial spike followed by an additional concave pattern of sales – as the result of indirect externalities of a product increasing with time as more complementary products become available. Sales at a given time expand to the following:

$$S(T)=\left[p+\left(\frac{q}{\overline{Q}}\right)\int_0^T S(t)dt\right]\left[\overline{Q}-\int_0^T S(t)dt\right]+ \\ +\left[\rho q_e\overline{Q}\int_t^T (S(t))^2dt\right]\left[\overline{Q}-\int_t^T S(t)dt\right]. \tag{7}$$

Further expansion and substitution results in the expression:

$$S(T) = p\overline{Q} + (q-p)Y(T) - \frac{q}{\overline{Q}}[Y(T)]^2 + \\ + \left[(1+\rho\overline{Q}^2)q_e[Y(t)]^2 - \rho q_e\overline{Q}[Y(t)]^3\right]_t^T.$$

(8)

When $q_e = 0$, equation (8) reverts to the Bass (1969) model.

In the special case, where the portion of sales attributable to inductive purchases depends upon the network externalities starts at $t = 0$, the expression becomes the following:

$$S(T) = p\overline{Q} + (q-p)Y(T) + \\ + \frac{(1+\rho\overline{Q}^3)q_e - q}{\overline{Q}}[Y(T)]^2 - \\ - \rho q_e\overline{Q}[Y(T)]^3. \tag{9}$$

The ability of the model to take the form as expressed in equation (9) is important for two reasons. First, the model reverts back to the original form as expressed in the Bass (1969) model, when there are no inductors present. Second, except in unusual circumstances the diffusion curve takes on the familiar unimodal form when externalities are present at the time of introduction of an innovation.

3. Testing model

Through regression analysis we test the fit of the model using black and white television, color television, video cassette recorder (VCR), and compact disc player (CD), telephones, and computer modems data. We obtained this information from the FastFacts database. Goldenberg, Libai and Muller (2002) used this same database to test their model. We attempted to restrict the analysis periods to excluded time intervals where repeat purchases would play a significant role.

We decided to compare the basic Bass model against our basic cubic model. Evaluation of basic the model serves as the best method of assessment, since it provides the simplest form of comparison. Besides, almost any enhanced version with the traditional squared term model can be applied to enhance the cubic term model. Following Bass (1967) we estimated the parameters utilizing least squares. We compare the model performance using the coefficient of multiple determination (r^2) and the mean squared error (MSE). The coefficient of determination compares the explained variance of the model's predictions against the total variance. MSE is a measure of the quality of an estimator, it not only assesses an estimator in terms of its variation, it also assesses the unbiasedness of models. The coefficient of multiple determination provide an indication of how well the model explains variance; while the MSE indicates that adding an extra term increases the explanatory power, instead of merely marginally reducing the sum of squared errors. The summary of our fit statistics are displayed in Table 1.

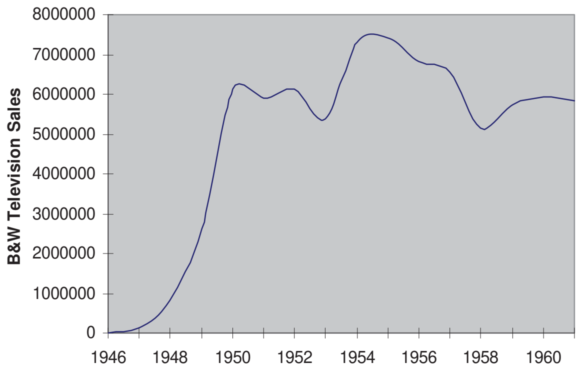
Table 1. The summary of the fit statistics

Product	Standard model r^2	Cubic model r^2	Standard model MSE	Cubic model MSE
Black & white television	0.50	0.66	2989456	2262148
Color television	0.90	0.96	2490553	980466
VCR	0.77	0.80	12008333	11168964
Compact disc (CD) players	0.98	0.98	8779198	7203856
Cellular phones	0.98	0.99	13879848	9029848
Computer modems	0.98	0.99	443296	61247

From Table 1 we can see that utilizing the cubic term enhances the fit of the model. With black and white television, the r^2-adjusted went from 0.50 to 0.66. Likewise, for video cassette recorders (VCR's) r^2-adjusted went from 0.77 to 0.80, and color television r^2-adjusted went from 0.90 to 0.96. With compact disk players, cellular phones, and computer modems the addition of the cubic term added only marginal to no value over the standard model.

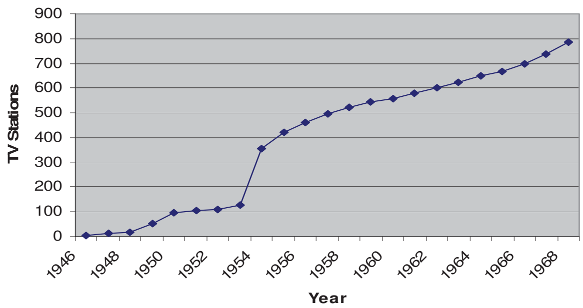
As stated in the development of this model, the cubic term describes the effect that product externalities have on the diffusion of products. The cubic term does not play a significant role when the products have sufficient externalities in place prior to product launch. There would be little or no benefit from using a cubic term for products that already have sufficient externalities, or products that require few if any externalities.

To illustrate the role externalities can have on the adoption of new products, we return to Bass (1969). In the original paper there was a distinct bi-modal diffusion pattern. The reader should examine Figures 1 and 2. In Figure 1, during the period from 1946 to 1950, the sales of black and white televisions in the US grew at an accelerating rate. After 1950, the sales of black and white televisions set taper-off. In Figure 2, we can see from the plot of the number of television stations in the US increased gradually between 1950 and 1953; we can also see during the period between 1953 and 1954, the growth in the number of television stations accelerated. Directly comparing the two figures reveals that the plateau in sales of black and white televisions corresponds to the plateau of the number of television stations. The sales spike in black and white television sales in 1954 corresponds to the spike in growth in the number of stations in 1954. The explanation for this spike in sales is quite simple. During the earlier period (from 1950 to 1953), television sales occurred mainly around major metropolitan centers where there were television stations. People in rural areas and small towns had no reason to buy televisions until programming became available. Later, during the period between 1953 and 1954, television stations began appearing in towns and smaller cities, where there were few if any television stations. Now people in smaller markets had a reason to purchase television sets, they now had programming available to them.



Source: Early Television Museum.

Fig. 1. Black & White television sales



Source: Early Television Museum.

Fig. 2. Black & white television stations

In the black and white television example, we can see that the sales hump corresponds to the availability of television stations. Instead of calculating the diffusion of innovation exclusively at product introduction, we incorporated the information concerning the number of television stations. Using equation (8), and setting t = 1954, we calculated the diffusion in two stages – normally between 1947 and 1953, and then using the cubic model between 1954 and 1968. Calculating diffusion utilizing the availability of television stations using the cubic model, the coefficient of multiple determination increased from 0.66 to 0.95. The coefficient of multiple determination for the original Bass (1969) model over the same period was 0.50. In this case, the cubic model has a higher level of explanatory power than the original Bass model.

Conclusion

This research directly relates to issues in innovation adoption and the implementation of diffusion of innovation models. By examining the role that network externalities play in the adoption of innovation, this work extends our ability to further explain how products diffuse within the marketplace. In managerial terms, firms can now have a better understanding of how an infrastructure of related products impacts the adoption of their innovation. Decision makers can utilize this model to perform sensitivity analysis to aid them in determining whether to subsidize or otherwise promote the development of externally related products and services.

Although the model described in this paper requires the estimation of a greater number of parameters than the basic Bass diffusion model, these parameters are easy to grasp. Likewise, the estimation of the parameters contained in this model requires no further information than that of the basic Bass diffusion model. As such, this model is a simple to use alternative to the basic model.

One of the major criticisms of equation-based models is the underlying assumption that products diffuse into fully connected and homogenous social networks (Peres, Muller and Mahajan, 2010). Another criticism is that diffusion theory depends upon interpersonal communication (Goldenberg et al., 2010; Van den Bulte & Lilien, 2001). While both of these are valid criticism, modelers of the diffusion process rarely encounter situations where adhering to these assumptions cause a significant adverse impact in estimating product diffusion. For most practical applications assuming that products diffuse within homogenous networks yield good estimates. Whether it is face-to-face communication with a neighbor, co-worker or friend; or computer-to-computer communication with someone half-way around the world, what is important is that the communication occurs among social actors. While it is a good idea to extend the definition of interpersonal influence to include social interdependence of all kinds, in many cases the extended definition has little affect on the conceptualization or implementation of innovation of diffusion models; as well as little affect on the forecast accuracy. Saying that the underlying assumptions of interpersonal communication among homogenous social networks is a valid but moot criticism is not to say that agency-based models of diffusion are not sometimes necessary. Rather, it is to say that the power and ability to utilize ABM comes at a cost-added complexity. Why sacrifice computational and conceptual simplicity and clarity unless it is necessary? For readers familiar with physics and engineering, utilizing ABM is akin to engineers calculating forces utilizing Einstein-Lorentz transformations rather that than Newtonian mechanics. In everyday situations, calculations done with Einstein-Lorentz transformations and Newtonian mechanics will yield the same results. It is not until objects move at rates approaching the speed of light will there be any differences in the results.

Sometimes complexity further removes analyst from the problems they seek to answer. For many problems, equation-based models provide an easy to use parsimonious method of studying, analyzing and addressing areas of inquiry. Rahmandad and Sterman (2008) summarized the conundrum when they said "Still, no matter how powerful computers become, limited time, budget, cognitive capabilities, and decision-maker attention mean modelers always face trade-offs: should they disaggregate to capture the diverse attributes of individuals, expand the model boundary to capture additional feedback processes, or keep the model simple so that it can be analyzed thoroughly?" Rather than utilizing diverse social structures to analyze multimodal diffusion patterns, analysts can look for simpler reasons, such as existence of sufficient network externalities.

The reader needs to understand that the above statements are not an attack on ABM. ABM is a very powerful tool. ABM gives researchers and practitioners the ability to systematically differentiate hypotheses concerning the behavior and interaction among agents in relationship to their effect on macro level systems. For a problem concerning the coordination of strategic interaction where multiple agents need to be distinguished, ABM is an excellent tool. In fact this paper complements and builds upon the work of Goldenberg, Libai and Muller (2002 and 2009) by explaining how populations can differ, yielding further support for multimodal diffusion.

References

1. Bass, F. (1969). A new product growth model for consumer durables, *Management Science*, 15, pp. 215-227.
2. Bayus, B. (1987). Forecasting sales of new contingent products: An application to the compact Disc Market, *Journal of Product Innovation Management*, 4, pp. 243-255.
3. Gartner Group (2002). Gartner hype cycle. Retrieved August 11, 2011. Avaliable from http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp.
4. Gatignon, H., Eliashberg, J. and Robertson, T. (1989). Modeling multinational diffusion patterns: an efficient methodology, *Marketing Science*, 8 (3), pp. 231-247.
5. Goldberg, J., Libai B. and Muller, E. (2002). Riding the saddle: how cross-marketing communications can create a major slump in sales, *Journal of Marketing*, 66 (April), pp. 1-16.

6. Goldenberg, J., Libai, B. & Muller, E. (2009). The chilling effects of network externalities, *International Journal of Research in Marketing*, 27 (1), pp. 4-15.
7. Goldenberg, J., Libai, B. & Muller, E (2010). The chilling effects of network externalities, *International Journal of Research in Marketing*, 27(1), pp. 4-15.
8. Hazhir, R. and Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models, *Management Science*, 54 (5), pp. 998-1014.
9. Horsky, D. (1990). A diffusion model incorporating product benefits, price, income and information, *Marketing Science*, 9 (4), pp. 342-365.
10. Jones, J. and Ritz, C. (1991). Incorporating distribution into new product diffusion models, *International Journal of Research in Marketing*, 8 (2), pp. 91-112.
11. Kalish, S. (1985). A new product adoption model with pricing advertising and uncertainty, *Management Science*, 2, pp. 135-160.
12. Lackmann, C. (1978). Gumpertz curve forecasting: A new product application, *Journal of the Market Research Society*, 20, pp. 45-47.
13. Lilien, G., Kotler, P. and Moorthy, K. (1992). *Marketing models*, Englewood Cliffs, New Jersey: Prentice-Hall.
14. Mahajan, V., Muller, E. and Bass, F. (1990). New product diffusion models in marketing: A review and directions for research. *Journal of Marketing*, 54 (1), pp. 1-26.
15. Mahajan, V., Muller, E., and Karen, R. (1984). Introduction strategy for new products with positive and negative word-of-mouth, *Management Science*, 3, pp. 1389-1404.
16. Mahajan, V., Muller, E. and Wind, J. (2000). *New product diffusion models*, New York: Kluwer.
17. Mahajan, V., and Peterson, R. (1978). Innovation diffusion in a dynamic potential adopter population, *Management Science*, 24, pp. 1589-1597.
18. Peres, R. Muller, E., Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions, *International Journal of Research in Marketing*, 27, pp. 91-106.
19. Peterson, R. & Mahajan, V. (1978). Multi-product growth models. In Sheth, J. (Ed.), *Research in Marketing*, Greenwich, CT: JAI Press, Inc, pp. 201-231
20. Rogers, E. (1962). *Diffusion of innovations*, 5th Edition New York: Free Press.
21. Rogers, E. (2003). *Diffusion of innovations*, 5th Edition New York: Free Press.
22. Rahmandad, H. and Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models, *Management Science*, 54 (5), pp. 998-1014.
23. Stremersch, S., Tellis, G., Franses, P., and Binken, J. (2007). Indirect network effects in new product growth, *Journal of Marketing*, 71 (3), pp. 52-74.
24. Sharif, M., and Ramanathan, K. (1981). Binomial innovation diffusion models with dynamic potential adopter population, *Technological Forecasting and Social Change*, 20, pp. 63-87.
25. Tanny, S. and Derzko, N. (1988). Innovators and imitators in innovation diffusion modeling. *Journal of Forecasting*, 7 (4), pp. 225-234.
26. Tornatzky, L. Klein, R. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings, *IEEE Transactions on Engineering Management*, EM-29 (1), pp. 28-45.
27. Van den Bulte, C., and Lilien, G. (2001). Medical innovation revisited: Social contagion versus marketing effort, *American Journal of Sociology*, 106 (5), pp. 1409-1435.