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The Bass Model of Diffusion: Recommendations for Use in Information Systems Research and Practice

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Abstract:

The Bass model (TBM), first introduced in 1969, has been used in several fields including sociology, economics, marketing, and communication studies to understand diffusion of products and innovations, but has received limited attention in information systems (IS) research and practice. TBM views diffusion as occurring through a combination of innovation (p) and imitation (q). Innovation and imitation describe the extents to which influences external to the population and influences internal to the population respectively affect diffusion. To encourage and enable greater use of TBM in IS research and practice, we describe an application process for using TBM and illustrate potential applications of TBM.

Keywords: Bass Model, Diffusion, Information Systems, Innovation, Imitation.

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INTRODUCTION

Considerable research has been conducted on the diffusion of innovations (Mahajan & Peterson, 1985; Rogers, 1995; Ruiz Conde, 2008). Two works—Rogers' (1962, 1983) innovation diffusion theory and the Bass model (TBM) (Bass, 1963, 1969)—have significantly affected diffusion research and practice. The empirically based innovation diffusion theory has received significant attention in information systems (IS) literature (Ilie, Van Slyke, Green, & Lou, 2005; Karahanna, Straub, & Chervany, 1999; Mustonen-Ollila & Lyytinen, 2003; Ramamurthy & Premkumar, 1995), but the mathematically based and empirically supported TBM has been less used. In contrast, TBM—either directly or indirectly (as the mixed influence model or through extensions)—has had considerable impact on practice and research in numerous fields, including sociology, economics, marketing, and organizational theory.

TBM can be used to: a) determine the diffusion patterns of IS innovations in a population, b) quantify the spread of IS innovations through the innovation and imitation coefficients, and c) predict the diffusion of future IS innovations using information about the spread of similar older innovations—none of which are known for many IS innovations. As IS expenditures continue to rise (e.g., Henderson, Kobelsky, Richardson, & Smith, 2010) and a number of IS innovations continue to be conceived, developed, and deployed in populations comprising organizations, teams, or individuals, it is important to plan for and predict diffusion, which TBM can enable.

This paper contributes to research and practice in the area of diffusion of IS innovations by encouraging the use of TBM and its variants. It pursues this goal by describing and illustrating potential applications of TBM (Bass, 1969). More specifically, we discuss potential application areas of TBM for IS using examples from literature, analyses of two datasets that we assembled for illustrative purposes, and further use of data from one study that has employed TBM (Teng, Grover, & Guttler, 2002). In addition, we draw on prior TBM literature, including 13 prior IS studies, to highlight ways in which TBM can be used in IS research and practice.

The remainder of the paper is organized as follows. The “diffusion research” section overviews existing diffusion research. The “Bass model” section describes TBM, and the “empirical methods for the Bass model” section introduces the estimation and analytical methods for TBM. The “review: the Bass Model in information systems research” section summarizes prior IS research using TBM. The “potential applications of the Bass model” section illustrates several applications of TBM. The paper ends with a conclusion section.

DIFFUSION RESEARCH

The diffusion of an innovation has been defined as the process through which innovation “is communicated through certain channels over time among the members of a social system” (Rogers, 1983, p. 5). The innovation could be any idea, practice, or object that is new to the members of the social system or population (Mahajan & Peterson, 1985), such as a medicine, an information technology (IT) product, or a software development approach. An adopter could be any entity such as an individual, a family, a firm, an industry, or a country. However, in any diffusion process, all members are assumed to be of the same broad type (e.g., all individuals or all firms). The social system, or population, for the diffusion includes all potential adopters of the innovation.

CONTRIBUTION

This paper contributes to information systems research in three ways. First, it examines the role of the Bass model in prior research on diffusion of information systems innovations. In doing this, it describes the Bass model, including the specification, data requirements, estimation methods, and guidelines. Second, the paper offers a narrative review of prior applications of the Bass model in information systems research, including methodological aspects. In this review, the paper identifies some limitations of some of the prior applications of the Bass model, despite the diversity in innovations, populations, and purposes. Finally, the paper illustrates potential applications of the Bass model in future research including understanding the nature of the diffusion pattern, identifying differences across innovations and populations, and highlighting differences between early adopters and later adopters. Overall, the paper should enable greater and more effective applications of the Bass Model in future information systems research.



A potential adopter experiences several stages such as knowledge, persuasion, decision, implementation, and confirmation when encountering and responding to an innovation (Rogers, 1995). In this stage model, the “decision” stage represents the potential adopter’s decision to adopt the innovation (or reject it if unconvinced). Since potential adopters may enter any stage at different points in time and continue in any stage for different lengths of time, the diffusion process extends over a period of time. Consequently, adopters are classified as innovators, early adopters, early majority, late majority, and laggards, with a frequency distribution of 2.5%, 13.5%, 34%, 34%, and 16%, respectively (Rogers, 1962, 1995; Brancheau & Wetherbe, 1990). The cumulative frequency distribution of adopters over time resembles an S-shaped curve (Rogers, 1962; Bass, 1969).

Several models have been proposed to explain diffusion. Critical mass theories propose that a critical mass of potential adopters is instrumental in enhancing diffusion (Markus, 1990). As the number of adopters increase in a population, a “critical mass” is reached after which diffusion is rapid as the remaining potential adopters to join the innovation’s bandwagon. Threshold models suggest that diffusion is dependent on threshold levels of potential adopters in the population (Granovetter, 1978). The “threshold” differs among the potential adopters and represents the proportion of the population who are already adopters. Diffusion proceeds as the threshold levels of potential adopters are met or exceeded by the proportion of adopters in the population. Homophily models argue that diffusion is facilitated by potential adopters occupying similar structural positions (Valente, 1995). According to homophily models, diffusion proceeds as potential adopters model themselves on others in their referent groups. Proximity models contend that diffusion is determined by the proximity of members to others in the population (Rice, 1993). Proximity may be defined variously as shared ties, shared positions, or shared spaces, with potential adopters modeling their responses to others who are proximate to them.

Influence models suggest that two types of communication channels affect potential adopters who are considering an innovation: mass media and interpersonal relationships (Rogers, 1995; Nilakanta & Scamell, 1990). Mass media channels such as magazines, advertisements, and brochures provide generic information about the innovation to a large number of potential adopters quickly. Interpersonal channels are considered to convey more specific and experiential information about the innovation among potential adopters that share ties with each other. Mass media channels are viewed as external influences, whereas interpersonal channels are considered to be internal influences to the population (Hu, Saunders, & Gebelt, 1997; Teng et al., 2002). Accordingly, if potential adopters are affected by mass media only or by interpersonal relationships only, diffusion may be explained using external influence models and internal influence models, respectively. However, in mixed influence models, potential adopters are subject to both mass media and interpersonal relationships (Rogers, 1962; Bass, 1969; Mahajan & Peterson, 1985; Hu et al., 1997).

THE BASS MODEL

An Introduction to the Bass Model

Following the work on diffusion of innovations (Rogers, 1962), Bass (1963) proposed the theoretical development for TBM and Bass (1969) provided empirical verification for TBM. Examining the purchases of a consumer durable over time, Bass (1969) distinguished between two types of buyers: innovators and imitators:

Innovators are not influenced in the timing of their initial purchase by the number of people who have already bought the product, while imitators are influenced by the number of previous buyers. Imitators “learn” in some sense, from those who have already bought (Bass, 1969, p. 217).

Innovators and imitators form the basis for innovation and imitation coefficients in TBM (See Figure 1). The innovation coefficient, p , is argued to represent innovation in the population (Bass, 1969; Burt, 1987; Florkowski & Olivas-Lujan, 2006; Mahajan, Muller, & Srivastava, 1990b). It reflects the extent to which adopters are influenced by their own intrinsic tendency to innovate and by factors beyond the population (including members of other populations and influences from “mass media” that affects all the populations). By contrast, the imitation coefficient, q , is argued to represent the extent to which the adopters emulate other members of the same population.

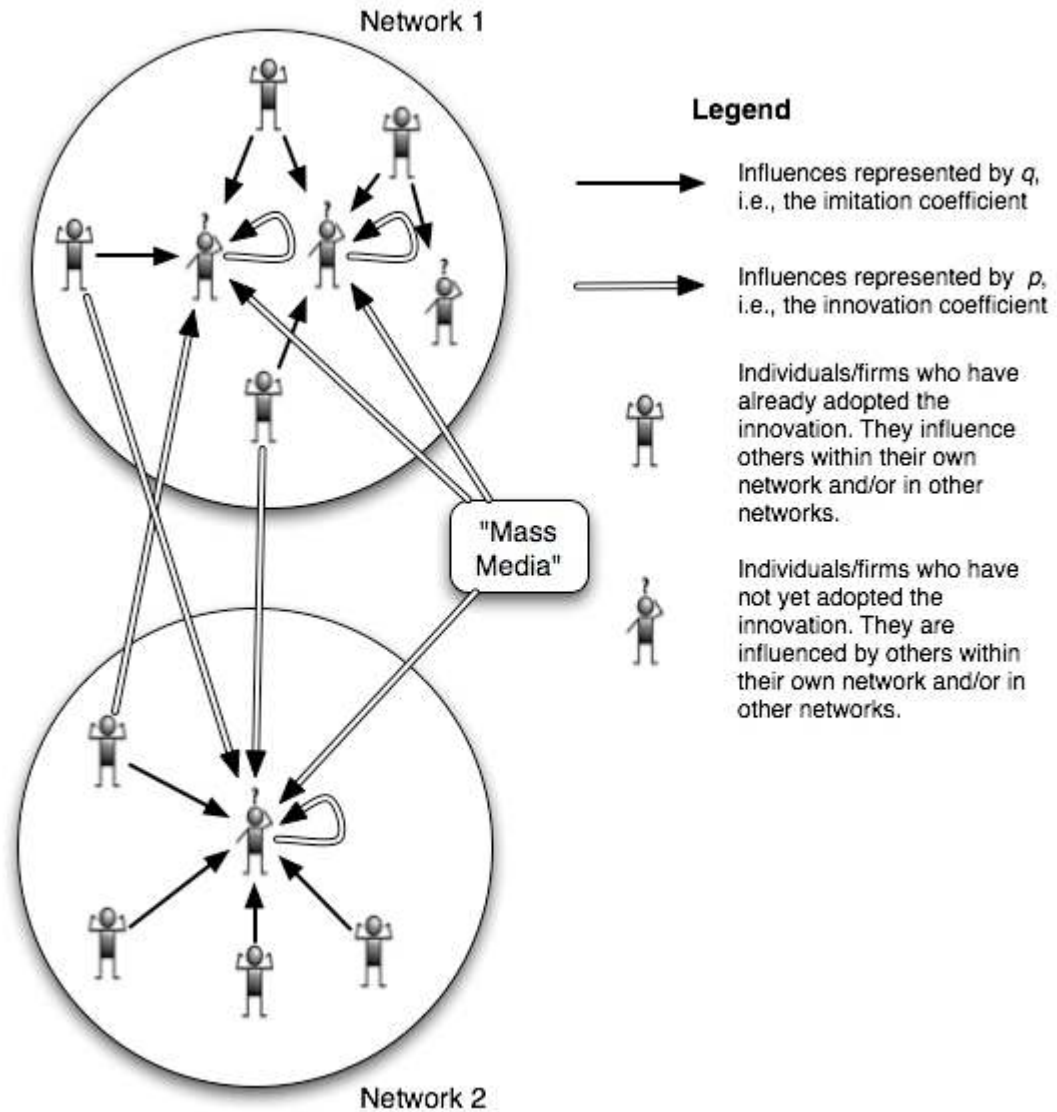


Figure 1: Innovation and Imitation coefficients

According to TBM, $f(t)$ is the probability of adoption at time t assuming adoption has not yet occurred, and $F(t)$ is the cumulative distribution:

$$f(t) / [1 - F(t)] = p + qF(t) \tag{1}$$

If time 0 is set to the launch of the product or the innovation so that cumulative adoption at the start is zero (i.e., $F(0) = 0$), then Equation 1 leads to the following distribution:

$$F(t) = \left[\frac{1 - \exp\{-(p+q)t\}}{1 + (q/p)\exp\{-(p+q)t\}} \right] \tag{2}$$

Consistent with prior works (e.g., Burt, 1987; Florkowski & Olivas-Lujan, 2006; Mahajan et al., 1990b), we view TBM in terms of adoption of an innovation. The potential adopters are part of a population of size M (which is the maximum possible number of adopters) (Srinivasan & Mason, 1986; Van den Bulte & Lilien, 1997), of which only a subset m represent the eventual adopters (or the market potential in the context of the purchase decision) (Tam & Hui, 2001; Van den Bulte & Lilien, 1997). If $n(t)$ is the number of new adopters at a point in time t , and $N(t)$ is the cumulative number of adopters at time t , then $n(t) = mf(t)$ and $N(t) = mF(t)$, and $m - N(t)$ are potential adopters who have not yet adopted. Therefore, equations (1) and (2) lead to equations (3) and (4), respectively:



$$n(t) = p[m - N(t)] + \frac{q}{m} N(t)[m - N(t)] \tag{3}$$

$$N(t) = m \left[\frac{1 - \exp\{-(p+q)t\}}{1 + (q/p)\exp\{-(p+q)t\}} \right] \tag{4}$$

The inflection point T^* and the corresponding peak number of new adopters $S(T^*)$ can be computed from the estimates of m , p , and q , as follows (Liu, Madhavan, & Sudharshan, 2005):

$$T^* = (p+q)^{-1} \ln(q/p) \tag{5}$$

$$S(T^*) = m(p+q)^2 / 4q \tag{6}$$

We can see from Equation 6 that, if $p > q$, T^* would be negative, and if $p = q$, T^* would be zero. In either situation, the curve for the number of new adopters over time would not exhibit an S-shaped curve, but instead the number of new adopters would be the highest at $t = 0$, and would decrease subsequently. The S-shaped curve would be observed if $p < q$.

Relationship between the Bass Model and Influence Models

Mahajan and Peterson (1985) and subsequently numerous other authors (e.g., Hu et al., 1997; Shao, 1999) call the Bass (1969) model the mixed influence model. The mixed influence model includes a parameter of external influence (a), which is determined by the adopter's intrinsic tendency to innovate and by communication from outside the population, and the parameter of internal influence (b), which represents the impact on the adoption of the innovation of the adopter's personal contact with previous adopters. The equations for the mixed influence model are identical to the above equations for TBM if the cumulative adoption at $t = 0$ is zero (i.e., $N(0) = 0$), with the innovation coefficient, p , being replaced by the parameter of external influence, a , and the imitation coefficient, q , being replaced by the parameter of internal influence multiplied by the market potential (i.e., bm).

Thus, the term $p[m-N(t)]$ in Equation 3 above represents adoptions resulting from innovation or from external influence, whereas the term $(q/m)N(t)[m-N(t)]$ represents adoptions resulting from imitation, or from internal influence through the interactions between cumulative adopters, $N(t)$, and non-adopters, $[m-N(t)]$. At the start of the diffusion process, the number of prior cumulative adopters, $N(t)$, is zero, and therefore the new adopters due to innovation is pm , whereas the number of new adopters due to imitation is zero. Over time, as the cumulative number of adopters increases, the number of new adopters due to innovation decreases, whereas the number of new adopters due to imitation first increases (because the increase in $N(t)$ has a greater effect than the decrease in $m-N(t)$), but, after an inflection point T^* , decreases (because the increase in $N(t)$ has a lesser effect than the decrease in $m-N(t)$).

TBM, or the mixed influence model, encompasses the internal influence model (same as TBM with $p = 0$) and the external influence model (same as TBM with $q = 0$). Prior studies (e.g., Hu et al., 1997; Teng et al., 2002) indicate that TBM outperforms these simpler models.

Assumptions of the Bass Model

TBM makes several assumptions. We classify these assumptions into three broad categories based on whether they relate to: (a) the innovation, (b) the context, or (c) modeling and estimation.

TBM's assumptions regarding the innovation are that (Bass, 1969; Mahajan & Peterson, 1985; Ruiz Conde, 2008): (a) the innovation is new for the population in question (i.e., diffusion begins with the cumulative number of adopters at zero), (b) the characteristics of the innovation or its perceived value do not change over time (i.e., potential adopters would value the innovation similarly regardless of the innovation's lifecycle or whether they are early or late adopters), or (c) the innovation, once adopted, is not replaced or discontinued by adopters.

TBM also makes some assumptions about the context (Bass, 1969; Mahajan & Peterson 1985; Ruiz Conde, 2008). More specifically, it assumes that: (a) when potential adopters in the population encounter the innovation at any point in time, they exercise one of two decisions (i.e., adopt or reject it), (b) the size of the population is fixed and is either known or can be estimated (i.e., changes to the population sizes due to turnover of actors is not handled), and (c) the potential adopters are assumed to be making their first-time decisions about the innovation (i.e., the model does not account for repeat decisions or new generations of the innovation).

Finally, TBM makes some assumptions about modeling and estimation (Bass, 1969; Ruiz Conde, 2008). More specifically, TBM assumes: (a) the availability of data on adoption by actors in the population since the innovation's inception (i.e., the model cannot generate estimates if data are missing), (b) that parameters p and q remain the same for the entire population, and therefore provides a single value of each parameter, (c) that the parameters p and q do not change over time (i.e., they represent a historical view of the diffusion activity over time), and (d) that the parameters p and q are sufficient for explaining diffusion (i.e., the model excludes decisional variables such as cost that potential adopters may consider). Appendix A summarizes extensions to TBM that relax some of the above assumptions.

EMPIRICAL METHODS FOR THE BASS MODEL

In this section, we discuss methodological aspects of using TBM on three aspects: (a) the data to be used for TBM, (b) the estimation methods, and (c) the results. In addition, we show a process for applying TBM.

Data

The data needed to apply TBM is rather simple. We highlight two types of situations when further considering the data required for TBM. Both situations require data about the number of new adopters in each time period but differ on the left truncation of data.

In the first situation, the data on number of new adopters is available without any left truncation (i.e., data on the number of new adopters in each period is available from the point in time when the innovation is introduced to the social system). The time period immediately preceding the first adoption should be set as $t = 0$, and Equation 4 should be used to estimate TBM. This is consistent with Bass's (1969) recommendation to set $t = 1$ for the first time period where the cumulative number of adopters exceeds pm .

The second situation involves left truncation (i.e., data on the number of new adopters in each period is available from some point in time after the innovation is introduced in the social system). In this situation, researchers need to identify when the innovation was first adopted in the social system. If the time of first adoption is known, the time period immediately preceding it may be viewed as $t = 0$ and Equation 4 may be used for estimation as Jiang, Bass, and Bass (2006) recommend. However, if the time of first adoption is not known, the virtual Bass model that Jiang et al. (2006) recommend may be used.

Estimation

TBM has been estimated using ordinary least square (OLS) regression (Bass, 1969), maximum likelihood estimation (MLE) (Schmittlein & Mahajan, 1982), and non-linear least squares (NLLS) estimation (Srinivasan & Mason, 1986). The OLS method enables the estimation of the model parameters but does not generate usable standard errors (Bass, 1969). The MLE method allows one to compute approximate standard errors for the model parameters largely based on sampling errors (Schmittlein & Mahajan, 1982). The NLLS method includes a mechanism to compute the total error that accounts for sampling and other sources of error (Srinivasan & Mason, 1986). The NLLS approach has generally been found to perform the best (Putsis & Srinivasan, 2000; Van den Bulte & Lilien, 1997). Srinivasan and Mason (1986) and Jain and Rao (1990) propose two approaches to using NLLS with TBM, which differ slightly in operationalization. Van den Bulte and Lilien (1997) compare the two approaches, and find Srinivasan and Mason's (1986) approach to be simpler and better in performance. Therefore, NLLS is considered appropriate for diffusion research, with the following operationalization by Srinivasan and Mason (1986) (Putsis & Srinivasan, 2000; Radas, 2006):

$$n(t) = N(t) - N(t-1) + \varepsilon(t) \quad (8)$$

Consistent with the earlier notation, $n(t)$ is the number of new adopters at a point in time t , whereas $N(t)$ is the number of cumulative of adopters at time t . $\varepsilon(t)$ is an independently distributed error term. Using Equations 4 and 8 leads to the following operationalization:

$$n(t) = m \left[\frac{1 - \exp\{-(p+q)t\}}{1 + (q/p)\exp\{-(p+q)t\}} \right] - m \left[\frac{1 - \exp\{-(p+q)(t-1)\}}{1 + (q/p)\exp\{-(p+q)(t-1)\}} \right] + \varepsilon(t) \quad (9)$$

Moreover, consistent with prior literature (e.g., Srinivasan & Mason, 1986; Van den Bulte & Lilien, 1997), the following constraints may be used: $0 \leq m/M \leq 1$, $q \leq 0$, $p > 0$, and $p > 0$, which imply $p \leq 1$ and $q < 1$. Excluding these constraints can cause difficulties in model convergence and also lead to bias in parameter estimation (Radas, 2006).



Dekimpe, Parker, and Sarvary (1998) found that parameter estimation biases result from using NLLS without these constraints.

Estimation of NLLS also requires specifying the starting values for m/M , p , and q . These starting values should be determined from the relevant prior literature. The statistical estimation for NLLS with the constraints and starting values can be conducted using constrained non-linear regression in SPSS or the NLIN procedure in SAS.

Results

NLLS estimation using Equation 9 produces several statistics including estimates of p , q , and m and also the R^2 for the equation, which indicates how well the data fits TBM. TBM's fit with the data can be further evaluated using the correlation between the actual and predicted number of new adopters in each time period (Bass, 1969), or by comparing the predicted and actual time taken to reach the peak number of new adopters (i.e., the inflection point). Another possibility is to test whether TBM improves on a null or white noise model (Hu et al., 1997) defined as follows (Mahajan, Sharma, & Bettis, 1988):

$$N(t) = N(t-1) + \varepsilon(t) \tag{10}$$

where $N(t)$ is the cumulative number of adopters at time t , and $\varepsilon(t)$ is the random error with normal distribution (i.e., $N(0, \sigma_\varepsilon^2)$). TBM is compared to the white noise model using a J-test (Hu et al., 1997; Loh & Venkatraman, 1992). The J-test produces a t -statistic and involves a simple linear regression below (Davidson & MacKinnon, 1989; Hu et al., 1997):

$$y_i - \hat{f}_i = \alpha(\hat{g}_i - \hat{f}_i) + \varepsilon_i \tag{11}$$

where \hat{f}_i and \hat{g}_i are the estimated values of the variable (i.e., the cumulative number of adopters) for the i^{th} observation by TBM and white noise model, respectively, where y_i is the value of the dependent variable (i.e., the observed cumulative number of adopters) for the i^{th} observation, and where σ_ε is the error term, which is assumed to be normally distributed (i.e., $N(0, \sigma_\varepsilon^2)$).

Applying the Bass Model

Figure 2 summarizes the overall process associated with using TBM. It includes three broad steps, discussed below.

Evaluation of the Appropriateness of TBM

It is important to first consider whether TBM is appropriate for the phenomenon under investigation. This involves addressing three questions (see Figure 2).

Question 1: Does the phenomenon involve multiple agents who adopt an innovation over time? TBM is appropriate for phenomena in which multiple agents (e.g., individuals, organizations) in one or more populations adopt an innovation (e.g., IT, IS, information, or knowledge) over time. If this is not the case, an alternative analytical approach should be employed.

Question 2: Is adoption a one-time decision related to one innovation? It should be reasonable to assume that adoption by each agent is a one-time decision related to one innovation. However, to some extent, whether this assumption is justified depends on the definitions of innovation and adoption in the relevant literature and appropriate for the empirical research. If it is not possible, the use of TBM cannot be justified and an extension of TBM, such as the adoption of successive generation of technologies (Norton & Bass, 1987), could be considered.

Question 3: Can longitudinal data be obtained on adoption in one or more populations? To use TBM, it should be possible to collect longitudinal data on when each agent adopts the innovation. Data on the number of new adopters is needed for several periods. If data is available for too few periods or if no data is available after the inflection point, results may be biased (Van den Bulte & Lilien, 1997). This assessment requires identifying the unit of time and the population boundary.

The unit of time needs to be decided prior to data collection, especially when data is collected periodically (e.g., using periodic surveys). If the data is available for a short duration (say, three years), the performance of TBM estimation can be improved somewhat by collecting and using data with shorter time intervals (say, quarters instead

of years, so as to increase the number of observation periods to 12 quarters rather than three years) (Van den Bulte & Lilien, 1997). When using secondary data, the availability of the data constrains the unit of time.

The boundary of the population should be identified before data collection if possible, but at least prior to data analysis. The population boundary should be drawn based on the level of analysis that is most appropriate based on theoretical considerations. However, the level of analysis has implications for the use of TBM. More specifically, using TBM at a more micro level enables comparison across populations and precludes innovation coefficient from being close to zero, but using TBM at an overly macro level might lead to the population being too small, and thereby preclude reliable estimation of TBM.

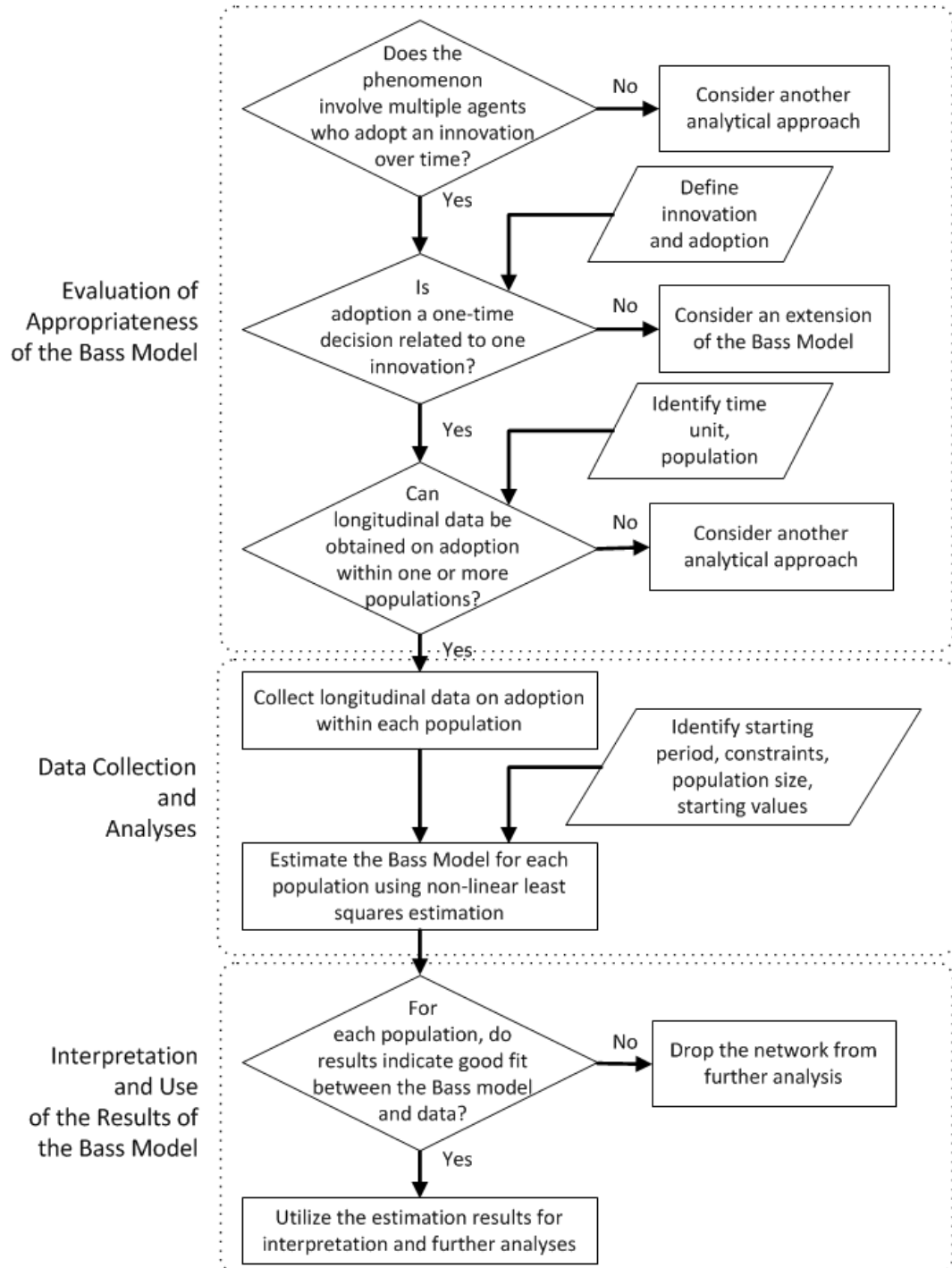


Figure 2: Process for Applying the Bass Model



Data Collection and Analyses

If the researchers are studying a phenomenon for which TBM is appropriate, they should collect longitudinal data on when each agent adopts the innovation. Several decisions—concerning the unit of time, the definition of the population, the starting period, left truncation, constraints, population size, and starting values—need to be made before estimating TBM. Also, the number of adopters in each time period for each population, and the starting point ($t = 0$) for each population as the time period prior to first adoption needs to be determined.

The estimation of TBM requires a constraint on m and starting values for m/M , p , and q (Dekimpe et al., 1998; Radas, 2006). The size of the population (i.e., M) needs to be identified to use the constraint on m . M is sometimes known (e.g., in surveys), and may otherwise be estimated prior to NLLS, which also requires the specification of the starting values for m/M , p , and q . Based on prior literature on TBM (Sultan, Farley, & Lehmann, 1996; Van den Bulte & Lilien, 1997), the starting values for m/M , p , and q may be 1, 0.01, and 0.40, respectively. Moreover, TBM should be estimated using NLLS as operationalized by Srinivasan and Mason (1986). This is consistent with prior literature (Putsis & Srinivasan, 2000; Van den Bulte & Lilien, 1997) and Equations 8 and 9 above.

Interpretation and Use of TBM Results

For each population, the fit between TBM and the data can be evaluated using a number of statistics. If TBM fits the data¹, the results of TBM estimation, including the estimates of p , q , m , m/M , and q/p ratios, the peak number of adopters, and the time taken to reach the peak number of adopters, can be used for several purposes that we discuss next.

First, the estimation results yield insights into the diffusion processes. It is possible to determine the extent to which an innovation diffuses as a result of external influence and internal influence, and the overall diffusion pattern in relationship to the S-shaped curve (e.g., Valente, 1993). Moreover, the results may be used to identify different types of adopters in the same population such as early adopters and laggards (e.g., Mahajan, Muller, & Bass, 1990a).

The second application area involves the diffusion of multiple innovations in the same population or the same innovation within multiple populations. In such circumstances, TBM results may be used to determine differences in diffusion patterns across innovations (e.g., Sultan et al., 1996) or populations (e.g., Talukdar, Sudhir, & Ainslie, 2002).

Finally, TBM is valuable in predicting the diffusion of innovations within a population (e.g., Bass, Gordon, Ferguson, & Gethen 2001). In this situation, estimates of the three parameters: m , p , and q are needed, which may be obtained through interviews or surveys of a sample of potential adopters in a target population, and through reasonable estimates of innovation and imitation coefficients based on prior similar innovations. Thus, the results obtained using TBM may be employed as data for predicting diffusion of similar innovations.

REVIEW: THE BASS MODEL IN INFORMATION SYSTEMS RESEARCH

We found thirteen studies that have used TBM in IS research². We summarize these studies in Appendix B, and provide the resulting parameter estimates in Appendix C. Eleven IS studies support TBM (or its equivalent, mixed influence model). One study (Tam, 1996) found extensions of TBM to perform better than TBM. A number of problems with the only other exception—(Loh & Venkatraman, 1992), which found the internal influence model to perform better than TBM—have been subsequently identified (Hu et al., 1997):

significant problems have been overlooked in the Loh and Venkatraman (1992) (referred to hereafter as LV92) study (p. 293).

Our analysis of the influence sources of IS outsourcing using the data set of 175 companies, as well as the LV92 data set of 60 companies, clearly indicates that the mixed influence model best describes the diffusion process of IS outsourcing (p. 299).

A closer examination of prior IS studies using the process for applying TBM (Figure 2) indicates some deviations in the appropriate application of TBM.

¹ If TBM is not a good fit, such population(s) may be dropped from further analysis involving TBM. Other models such as the Von Bertalanffy model, Gompertz function, internal influence model, external influence model, and threshold model (e.g., Hu et al., 1997; Valente, 1995; Mahajan & Peterson, 1985) may be considered.

² In identifying the papers, we excluded four that mention TBM but do not report estimates (Cha, Durcikova, & McCoy, 2005; Chang, Yin, & Chou, 2008; Chu, Wu, Kao, & Yen, 2009; Liberatore & Breem, 1997).

Innovations

Prior studies have generally examined the diffusion of IT products (e.g., electronic mail, computers) and practices (e.g., outsourcing) using TBM. Two studies (Hu et al., 1997; Loh & Venkatraman, 1992) examine the diffusion of IT outsourcing. Six studies examine the diffusion of electronic mail (Astebro, 1995), mainframes (Tam, 1996; Tam & Hui, 2001), minicomputers (Tam & Hui, 2001), personal computers (Tam & Hui, 2001), automated teller machines (Dos Santos & Peffers, 1998), expert systems (Shao, 1999), computer-aided design (Kale & Ardit, 2005), and mobile Internet (Wang, Ku, & Doong, 2007). Finally, Florkowski and Olivas-Lujan (2006), Kim and Kim (2004), Teng et al. (2002), and McDade, Oliva, and Thomas (2010) examine the diffusion of eight, 17, 19, and 39 different ITs, respectively.

Populations

The most common populations in prior studies comprise firms, although a few studies examined populations of individuals and households. Of these few studies, two examine diffusion across individuals (Astebro, 1995; Shao, 1999), one examines diffusion across individuals and firms (Tam & Hui, 2001), one examines diffusion across firms and households (Kim and Kim 2004), two assess diffusion across banks (Dos Santos & Peffers, 1998; Wang et al., 2007), and the remaining seven analyze diffusion across a variety of firms. Although their primary focus is on United States, studies also investigate diffusion in Canada (Florkowski & Olivas-Lujan, 2006), Britain (Florkowski & Olivas-Lujan, 2006; Shao, 1999), Ireland (Florkowski & Olivas-Lujan, 2006), Sweden (Astebro, 1995), Korea (Kim & Kim, 2004), Turkey (Kale & Ardit, 2005), and Taiwan (Wang et al., 2007).

Adoption Decisions

Eleven studies seem to have used IT in contexts involving one-time decisions regarding adoption, for which TBM may be relevant. Of the two exceptions, Astebro (1995) examines the diffusion of the usage of electronic mailboxes by individuals over time by tracking access to electronic mailboxes and counting the number of electronic mailboxes that were accessed twice or more in a week. This context may be a bit different than for which TBM was initially constructed because individuals would go back and forth between being adopters and non-adopters depending on whether they used electronic mailboxes in a given week. The remaining study, Florkowski and Olivas-Lujan (2006), seems consistent with TBM in some situations (i.e., the diffusion of an individual human resource IT because each firm would have adopted that particular IT only once) but not in others (i.e., the diffusion of all human resource ITs; since this implies each firm potentially adopting up to eight different ITs, each firm can make multiple adoption decisions over time, which is inconsistent with TBM).

Data Collection

A variety of data collection methods are seen in prior research employing TBM. These include public announcements (Hu et al., 1997; Loh & Venkatraman, 1992), secondary sources (Tam, 1996), interviews (Shao, 1999), telephone interviews (Kale & Ardit, 2005), surveys (Teng et al., 2002), and the tracking of electronic mailboxes (Astebro, 1995).

Modeling Choices

Two formulations for TBM exist in prior literature. The first, as shown in Equation 7, uses p and q . The second, as documented in Mahajan and Peterson (1985), uses a and b as the coefficients of external influence and internal influence, respectively. Although p and a are interchangeable, q and b are not; instead q is equivalent to bm , where m is the market potential. Three prior studies in IS (Dos Santos & Peffers, 1998; Hu et al., 1997; Wang et al., 2007) use Equation 7, but replace q with qm (instead of bm). Although the results of such studies are appropriate, interpreting them requires recognizing that q is that coefficient of internal influence (for which b is the more common symbol), and not the imitation coefficient (which q commonly represents, as per Bass (1969) and numerous others). Failure to do so would lead to these results being used incorrectly to predict innovation and imitation coefficients. The inappropriate use of these symbols may also cause confusion when comparing these coefficients: p and q can be compared, but a should be compared with bm , not with b .

Correction for Left Truncation

As Appendix B shows, no correction for left truncation of data is needed in six studies because they use data starting from the introduction of the innovation within the relevant social system. However, left truncation is a potential problem in the other seven studies. One study (Loh & Venkatraman, 1992) does not apply any correction for left truncation (as seen from Equation 10 on its page 345). Three studies (Kale & Ardit, 2005; Kim & Kim, 2004; McDade et al., 2010) do not seem to have corrected for left truncation. The remaining three IS studies using TBM (Astebro, 1995; Dos Santos & Peffers, 1998; Hu et al., 1997) use Equation 9 for Mahajan and Peterson's (1985) approach to addressing the left-truncation problem. Although these papers have used the approach that seemed

appropriate at that point, their results may be affected by the problems associated with Mahajan and Peterson's (1985) approach that Jiang et al. (2006) have identified.

Use of Constraints in the Model

Excluding the constraints of TBM can lead to bias in parameter estimation (Dekimpe et al., 1998; Radas, 2006). It is difficult to ascertain whether or not ten studies use these constraints, but other three studies appear to have not used them because they report negative estimates of p either for TBM (Tam & Hui, 2001) or for external-influence model (Dos Santos & Peffers, 1998; Wang et al., 2007).

Purposes

These studies use TBM for a number of different objectives. All the studies use TBM to understand the diffusion process, but three studies (Dos Santos & Peffers, 1998; Shao, 1999; Wang et al., 2007) use TBM **only** for this purpose. Some studies use TBM to compare diffusion between two time periods (Hu et al., 1997; Loh & Venkatraman, 1992), across countries (Florkowski & Olivias-Lujan, 2006); across ITs (Florkowski & Olivias-Lujan, 2006), and across departments in the same firm (Astebro, 1995). Two studies use the parameters resulting from TBM to develop clusters of ITs (Teng et al., 2002) or as dependent variables in regression analysis (Tam & Hui, 2001).

POTENTIAL APPLICATIONS OF THE BASS MODEL

To foster the use of TBM in future research, we here discuss and illustrate potential applications of TBM in IS. In these applications, innovation is viewed with respect to the adoption but not the development of IS. The following research questions guide the data analysis and discussion relating to the applications of TBM:

- a) What are the patterns of diffusion of IS innovations? Our proposition is that the pattern of diffusion would correspond to the S-shaped curve as generally proposed in the diffusion literature (Rogers, 1995; Bass, 1969).
- b) How does diffusion differ across different i) innovations and ii) populations? Our proposition is that the pattern of diffusion may differ across innovations and across populations. Such differences occur due to several reasons and usually manifest in terms of differences in the levels, innovation and imitation coefficients, or speed of diffusion. Innovations may differ in their characteristics, capabilities, and attractiveness to the potential adopters (e.g., Rogers, 1995); for instance, the electronic data interchange (EDI) systems enable communication between organizations, whereas the warehouse management system enables an organization to automate its internal warehouse operations. Populations may differ in their practices, policies, and norms; for instance, the healthcare industry is subject to certain regulations that may not be prevalent in other industries, whereas the finance industry deals with information products to a greater degree than other industries.
- c) How do the early adopters and later adopters in a population differ? Our proposition is that there may be significant differences between early adopters and later adopters of an innovation. Potential adopters may be characterized using attributes such as size, resources, efficiency, and competing industry (e.g., Grover, Fiedler, & Teng, 1997), and these characteristics are expected to differ between early and late adopters of the same adoption.

To illustrate potential applications of TBM, we assembled two illustrative datasets: (1) a dataset (EC_FIRM) based on annual *InformationWeek 500* surveys from 1999 to 2003 to examine the diffusion of electronic commerce (EC) applications across firms represented in these annual surveys, and (2) a dataset (SC_FIRM) based on annual *InformationWeek 500* surveys from 1999 to 2005 to examine the diffusion of electronic supply chains (SC). Appendix D provides further information about these two datasets and the computation of the associated population size (i.e., M). Our analysis included 536 organizations for EC_FIRM and 588 organizations for SC_FIRM. In addition, we conduct some additional analyses using published data from a prior IS study using TBM: Teng et al. (2002).

For TBM analysis of the two datasets, we determined the number of adopters in each year using the year of adoption for each organization. For each technology, we determined the initial year of adoption in the population and hence left-truncation was not an issue. We used Equation 2 as the basis for TBM estimation. We obtained the parameter estimates by using NLLS (in SPSS), which was completed with the recommended starting values. We examined the correlation between predicted and observed number of adopters to determine the extent to which TBM fits the data. We compared TBM estimates with the white noise model (Equation 11) as well. We also obtained the time period for the peak number of adopters (Equation 5) and the number of adopters at the peak time period (Equation 6). Table 1 shows the results for the diffusion of EC and SC technologies across organizations.

Examination of Diffusion Processes

The nature of the diffusion process (e.g., Burt 1987) may be studied through the innovation coefficient (or external influence), imitation coefficient (or internal influence), market potential, the peak number of adopters, and the time taken to reach the peak number of adopters.

Table 1: Results for Diffusion across Populations

Panel A: Electronic Commerce									
Industry	Period ^b	Population size ^c (adopters)	p	q	m	R^2 (t-statistic for J test) ^d	Correlation between observed and predicted $n(t)$	Inflection point ^e : predicted (observed)	Peak adopters: predicted (observed)
Manufacturing	1989-2003	253 (211)	0.0001	0.9999	0.794	0.704 (5.346***)	0.887***	9.21 (10)	52.76 (70)
Service	1994-2003	81 (61)	0.013	0.987	0.764	0.633 (3.718***)	0.817***	4.39 (5)	15.45 (21)
Finance/ information	1989-2003	102 (92)	0.0001	0.9998	0.821	0.666 (4.897***)	0.886***	9.21 (9)	23 (24)
Wholesale/ retail trade	1989-2003	100 (88)	0.0001	0.9998	0.848	0.748 (5.971***)	0.911***	9.21 (10)	22 (25)
Overall	1989-2003	536 (452)	0.0001	0.9999	0.803	0.74 (5.847***)	0.910***	9.21 (10)	113.01 (136)
Panel B: Electronic Supply Chains									
Industry	Period	Population size (adopters)	p	q	m	R^2 (t-statistic for J test)	Correlation between observed and predicted $n(t)$	Inflection point: predicted (observed)	Peak adopters: predicted (observed)
Manufacturing	1991-2005	245 (197)	0.001	0.84	0.751	0.653 (4.756***)	0.869***	8.02 (8)	41.47 (51)
Service	1993-2005	97 (63)	0.004	0.996	0.619	0.65 (3.358***)	0.858***	5.54 (6)	15.81 (21)
Finance/ information	1989-2005	148 (85)	0.0002	0.815	0.565	0.497 (3.72***)	0.718***	10.20 (10)	17.83 (24)
Wholesale/ retail trade	1991-2005	98 (86)	0.001	0.999	0.872	0.707 (5.383***)	0.868***	6.91 (8)	21.52 (31)
Overall	1989-2005	588 (431)	0.0001	0.956	0.675	0.674 (5.382***)	0.871***	9.59 (10)	103.03 (127)

^a We included the following constraints: $0 \leq m \leq M$; $0 < p \leq 1$; $0 \leq q \leq 1$; $p + q < 1$. Starting values for p , q , and m were 0.01, 0.40, and 0.90, respectively.

^b For each population (i.e., industry sector and overall sample), period starts with the year before the first adoption in that population.

^c We constrained m (i.e., the market potential, or the number of eventual adopters) as follows: $0 \leq m \leq M$. Additionally, we included the following constraints: $0 < p \leq 1$; $0 \leq q \leq 1$; $p + q < 1$. Starting values for p , q , and m are 0.01, 0.40, and 0.90, respectively.

^d Significance levels (one-tailed) for t -statistics associated with J-tests are indicated as follows: ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

^e Inflection points are given in number of years, with the starting period given in the second column of this Appendix as $t = 0$.

Figure 3 graphically illustrates the observed and TBM-predicted diffusion patterns for EC and SC technologies examined in this study. For each technology in our study, we used the parameter estimates for p , q , and m in Equation 4 and obtained the cumulative number of adopters predicted by TBM. As Figure 3 shows, the diffusion patterns for the two technologies resemble an S-shaped curve although the population size, innovation coefficient, and imitation coefficient differ between the two technologies. For both EC and SC technologies, diffusion was consistent with TBM's predictions until about the inflection point after which there was a slowdown before an eventual upswing in diffusion rates. The unexpected slowdown after the inflection point could have been due to the

reallocation of organizational resources in the wake of the Y2K problem that threatened computing operations before the turn of the 21st century (Gowan, Jesse, & Mathieu 1999). However, diffusion sped up again after the brief slowdown as organizations turned their attention back to the EC and SC technologies coinciding with the e-commerce and dot-com movement (Evans & Wurster, 2000).

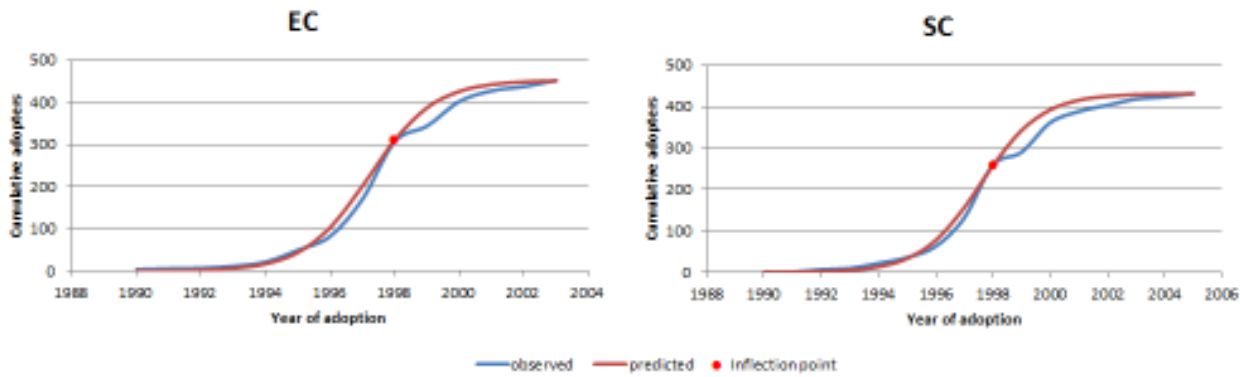


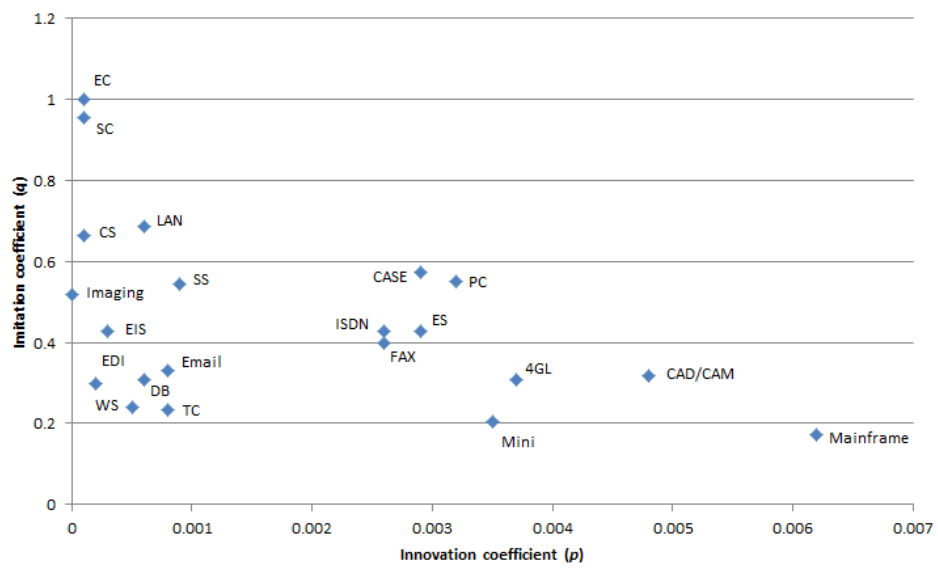
Figure 3: Diffusion Patterns for EC and SC Technologies

TBM indicated that the peak number of adopters would be reached in 9.21 and 9.59 years respectively for EC_FIRM and SC_FIRM, which is close to the observed inflection points (ten years for both innovations). Further, the peak number of adopters predicted by TBM for both EC and SC technologies were 113 and 103 adopters, respectively, which was somewhat lower than the observed peak number of adopters (136 and 127) for the two technologies, respectively. The difference between the predicted and observed peak number of adopters may be attributed to two reasons. In the early time periods, organizations may have been driven to adopt the EC and SC technologies at a much faster rate due to the attractiveness of the technologies and their potential to offer first-mover advantage, improve efficiencies, and increase customer reach (e.g., Evans & Wurster, 2000), which may have increased the observed peak number of adopters. In the later time periods, organizations may not have adopted the EC and SC technologies as fast due to resource demands in other areas such as the Y2K phenomenon, which may have reduced the predicted peak number of adopters since TBM uses data available across all time periods. Collectively however, the predictions provided by TBM may be used as conservative estimates to plan for diffusion of innovations.

Examination of Differences across Innovations

The parameters resulting from TBM may be used to compare diffusion processes across different innovations. Table 1 shows that the values of p were 0.0001 and 0.0001, and that the values of q were 0.999 and 0.956 respectively for the EC and SC technologies in our study. Figure 4 shows a plot of the two technologies in our analysis and those reported by Teng et al. (2002) based on values for p and q .

The values of p for EC and SC technologies were **lower** than the values reported by Teng et al. (2002) but somewhat comparable to the values reported in prior IS studies (see Appendix C). Similarly, the values of q for EC and SC technologies were considerably **higher** than the values reported by Teng et al. (2002) and prior IS studies (see Appendix C). The values of p may be lower and the values of q may be higher for EC and SC technologies due to several reasons. EC technologies were virtually radical Internet-based innovations that introduced new ways in which the organizations may sell products, provision services, or reach customers (e.g., Evans & Wurster, 2000), whereas SC technologies were generally complex inter-organizational information systems that force adopting organizations to examine and possibly alter their intra- and inter-organizational business processes (e.g., Ramamurthy & Premkumar, 1995). Consequently, some firms may decide never to adopt these technologies. Consistent with this argument, the values for market potential reveals that the two technologies may not diffuse to all members of the population ($m = 0.803$ and 0.675 for EC and SC, respectively). Moreover, the newness and complexity of the innovation pose significant knowledge barriers to organizational adoption (Attewell, 1992). As a result, relatively fewer organizations that are proactive about new technologies have the desire to experiment with new technologies, and the capacity to overcome knowledge barriers (by applying internal expertise or renting external expertise) are likely to become innovators (e.g., Attewell, 1992; Rogers, 1995; Ifinedo, 2011). Over time, however, the remaining organizations encounter opportunities to learn more about the new technology, evaluate the adoption experiences of innovators, and identify efficient ways to apply the new technology, and would become imitators (e.g., Kraatz, 1998).



This study: SC: Supply chain, EC: Electronic commerce
 Teng et al. (2002): LAN: local area network, CS: client/server, CASE: computer-aided software engineering, PC: personal computer, SS: spreadsheet, EIS: executive information system, ISDN: integrated services digital network, ES: expert systems, DB: large-scale relational databases, CAD: computer-aided design, CAM: computer-aided manufacturing, EDI: electronic data interchange, WS: workstation, 4GL: fourth-generation languages.

Figure 4: Comparison of EC and SC Technologies with Others

Examination of Differences across Populations

Parameters obtained from TBM can be used to compare diffusion of innovations across different populations. We drew the boundaries of the population for our analysis using industry groups as clusters. Figure 5 shows the graphs of diffusion patterns across different clusters for EC and SC technologies.

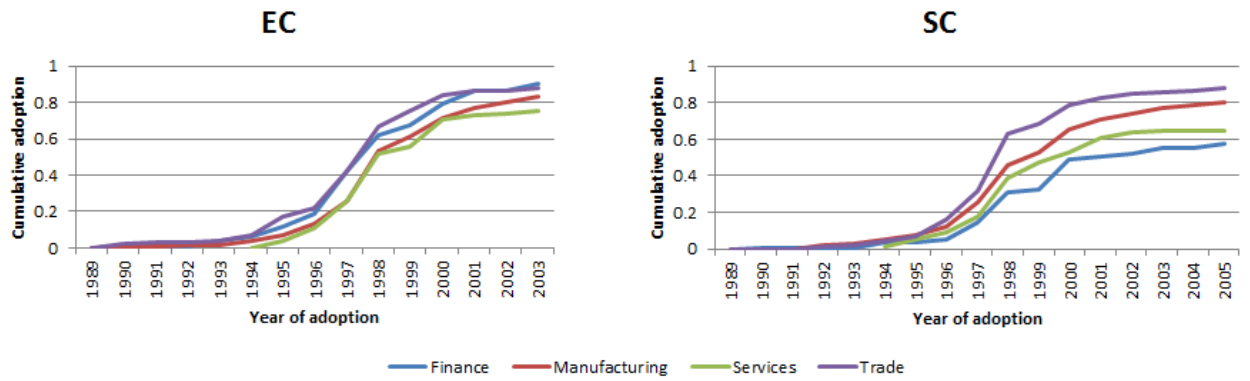


Figure 5: Diffusion of EC and SC Technologies in Different Populations

We estimated p and q across four industry groups³ (i.e., manufacturing, service, finance/ information, and wholesale/retail trade) for EC_FIRM and SC_FIRM data (see Appendix D). TBM exhibits good fit with these data sets. The values for p and q showed some differences across the industry groups: p ranged from 0.0001 to 0.013 for EC and from 0.0002 to 0.001 for SC, while q ranged from 0.987 to 0.999 for EC and from 0.815 to 0.999 for SC. The market potential values for EC ranged from 0.764 (service) to 0.848 (wholesale/retail trade) and for SC from 0.565 (finance/information) to 0.872 (wholesale/retail trade).

For EC technologies, the service industry exhibited the highest innovation ($p = 0.013$) whereas the other three industries showed lower innovation ($p = 0.0001$). The service industry (e.g., Hilton hotels) may have considered EC

³ We started with the traditional classification of organizations into the manufacturing and service sectors (e.g., Damanpour, 1991) and then separated wholesale/ retail trade organizations due to non-transformation of products and finance/information organizations due to information products.



technologies as another channel by which to reach new markets and attract customers from different regions (Evans & Wurster, 2000). However, the other industries may have exhibited relatively slow response to EC due to different reasons. For instance, the manufacturing (e.g., Ford Motors) and wholesale trade (e.g., W.W. Grainger) industries rely on retail stores or other distribution outlets, whereas the retail trade industry (e.g., Kroger Corporation) may consider their brick-and-mortar stores to be the focal points of their operations. These industries may not have viewed EC technologies favorably when it was new possibly due to fears of disintermediation and cannibalization (Evans & Wurster, 2000).

The manufacturing, wholesale/retail trade, and finance/information industries had higher imitation ($q = 0.999$) and the service industry showed a slightly lower imitation ($q = 0.987$). However, the level of imitation is comparable across all industries. This may indicate that EC technologies posed challenges to organizations across various industries, quite possibly due to the ways in which it questioned traditional ways of conducting business (Evans & Wurster, 2000). Hence, it is likely that organizations engaged in efforts to better understand the new technology and quite possibly to learn from the experiences of other organizations that may have already adopted it (e.g., Kraatz, 1998). Over time, however, organizations may have adopted the EC technology due to various reasons including their own positive evaluations and institutional pressures to gain legitimacy (e.g., Rogers, 1995; DiMaggio & Powell, 1983).

For SC technologies, the service industry exhibited the highest innovation ($p = 0.004$) whereas the finance/information industry had the lowest innovation ($p = 0.0002$). The wholesale/retail trade and manufacturing industries showed similar levels of innovation ($p = 0.001$). Since the SC technologies are largely designed to enable information sharing between supply chain partners, they provide greater benefits to organizations that interact with several partners for their everyday operations (Wong, Lai, & Cheng 2011). The interactions with partners are transaction-intensive involving a high frequency of purchases from suppliers and orders from customers, which may adversely affect organizational efficiency (Narayanan, Maruchek, & Handfield, 2009). Organizations in the manufacturing, wholesale/retail trade, and service industries, which typically deal with a number of partners, are likely to consider SC technologies to eliminate inefficiencies in their interactions with partners.

The finance/information and manufacturing industries had lower imitation ($q = 0.815$ and 0.84 , respectively), whereas the wholesale/retail trade and service industries exhibited higher imitation ($q = 0.999$ and 0.996 , respectively). Despite the slight differences, the imitation coefficients are comparable and indicate that organizations across various industries were faced with significant learning curves due to the complexity of implementing SC technologies (Attewell, 1992). SC technologies that exist in different forms such as interorganizational systems and electronic data interchange systems require organizations to manage information sharing, document standards, and data translation with *each* link with their many partners (Grover & Saeed, 2007; Iskander, Kurokawa, & LeBlanc, 2001). Organizations may require external expertise to successfully implement SC technologies.

Examination of Differences across Early and Later Adopters

TBM estimates can be utilized to frame an analysis of the individual adopters (i.e., individuals, firms, and so on, depending on the population) for additional insights regarding the diffusion process. We used the EC_FIRM and SC_FIRM datasets to further illustrate the use of TBM to examine differences across early and later adopters in the two datasets.

We first classified each adopter in the EC_FIRM and SC_FIRM datasets as an early adopter or a later adopter with respect to each technology. For each technology, we used TBM estimates for p and q to compute the inflection point (see Appendix D) and then identified early adopters and later adopters as firms that adopted the technology before and after the predicted inflection point, respectively (Rogers, 1995). There were 171 early adopters and 281 later adopters among the 452 adopters of EC, and there were 133 early adopters and 298 later adopters among the 431 adopters of SC. We found that 352 organizations adopted both EC and SC technologies during the study periods: 79 organizations were early adopters and 121 organizations were later adopters of both technologies. Further, 60 organizations were early adopters of EC but later adopters of SC and 92 organizations were early adopters of SC but later adopters of EC. We also found that early adopters and later adopters are not independent ($\chi^2 = 6.26$, $p < 0.05$). Moreover, results showed that 137 organizations adopted EC before SC technologies with an average earliness of 2.56 years; 107 adopted EC and SC in the same year; and 108 organizations adopted SC before EC technologies with an average earliness of 2.18 years.

For each adopter, we gathered data on the following variables where possible for the year prior to its adoption of the respective technologies: organization size (i.e., number of employees), resources (i.e., assets), efficiency (i.e., return on assets: ROA), and competing industry (i.e., finance/information, manufacturing, service, or wholesale/retail trade). Table 2 displays the distribution of early adopters and later adopters (along with non-adopters) across the four industry groups for both technologies. The results show that the competing industry was related to the

classification of early adopters and later adopters for both technologies ($\chi^2 = 11.50$ and 47.54 for EC and SC respectively, $p < 0.05$). The manufacturing industry had a smaller proportion of early adopters of EC (25%) than SC (45%), whereas all the other industries exhibited a larger proportion of early adopters of EC than SC.

Table 2: Early Adopters and Later Adopters across Industries

Type of innovation	Cluster	Finance	Manufacturing	Service	Wholesale/retail trade	Total	χ^2
EC	Early adopters	43 (42%)	65 (25%)	21 (26%)	42 (42%)	171	11.50***
	Later adopters	49 (48%)	146 (58%)	40 (49%)	46 (46%)	281	
	Adopters	92	211	61	88	452	8.83***
	Non-adopters	10	42	20	12	84	
	Total	102	253	81	100	536	
SC	Early adopters	46 (31%)	113 (45%)	17 (17%)	16 (16%)	133	47.54***
	Later adopters	39 (26%)	84 (34%)	46 (47%)	70 (71%)	298	
	Adopters	85	197	63	86	431	39.28***
	Non-adopters	63	48	34	12	157	
	Total	148	248	97	98	588	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Percentage in parentheses are based on total

We conducted t-tests to compare the mean values of organization size, resources, and efficiency between early adopters and later adopters. Table 3 shows those results, which indicate that there were no differences between early adopters and later adopters on organization size and resources for both EC and SC technologies. However, early adopters and later adopters of both technologies significantly differed in the efficiency, with early adopters of EC and SC exhibiting greater ROA than imitators ($t = 2.19$ and 2.47 for EC and SC, respectively, $p < 0.05$).

Table 3: Differences between Early Adopters and Later Adopters

Type of innovation	Cluster	#Employees	Assets	ROA	$t_{\#Employees}$	t_{Assets}	t_{ROA}
EC	Early adopters	49.25 (104)	19266.04 (106)	5.28 (106)	1.10	0.36	2.19**
	Later adopters	35.96 (169)	17021.10 (176)	3.26 (176)			
SC	Early adopters	40.73 (117)	15992.22 (121)	5.41 (121)	0.38	-0.18	2.47**
	Later adopters	37.04 (155)	16863.24 (161)	2.71 (161)			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Sample size shown in parentheses
#Employees in 000s, Assets in Million US\$, ROA: Return on assets

We conducted the above analysis by industry as well. For EC technologies, we found no significant differences between the early adopters and later adopters in the wholesale/retail and finance/information industries. These results indicate that organizations in these industries adopted EC regardless of their size, resources, or efficiency, possibly exploiting the promise of greater reach and richness of the technology (Evans & Wurster, 2000). However, there were significant differences between early adopters and later adopters in the manufacturing and service industries. The early adopters in the manufacturing industry were more efficient ($t_{ROA} = 2.08$, $p < 0.05$) and perhaps larger ($t_{\#Employees} = 1.70$, $p < 0.10$), while those in the service industry possessed lesser resources ($t_{Assets} = -2.07$, $p < 0.05$) compared to later adopters. It seems that early adopters in the manufacturing industry aimed to employ EC technologies for greater efficiencies, whereas those in the service industry found EC technologies to level the playing field for them (Evans & Wurster, 2000). For SC technologies, there were no significant differences between

early adopters and later adopters in any industry except perhaps the manufacturing industry that showed early adopters to be relatively larger organizations ($t_{\#Employees} = 1.69, p < 0.10$). These results show that organizations across various industries engage with SC technologies regardless of their size, resources, or efficiency, perhaps in support of their own strategies or in response to the power of partners (e.g., Grover, 1993).

Examination of the Drivers of Diffusion

TBM parameters may be used as dependent variables in regression or structural equation models to examine factors affecting the innovation and imitation in the diffusion of new products (e.g., Bayus, 1992; Kohli, Lehmann, & Pae, 1999). Alternatively, correlation analysis may be conducted to assess the association between TBM parameters and other factors that may affect the diffusion process. Since TBM parameters are population-level measures, it becomes necessary to accumulate the results⁴ from a large number of populations⁵ in order to conduct analyses needed to identify the drives of the diffusion.

Examination of the Diffusion of a Future Innovation

TBM can be used to forecast the diffusion of a future innovation (Bass et al., 2001) prior to launch in a population. In this situation, estimates of the three TBM parameters (m , p , and q) are needed (Bass et al., 2001). We have summarized these coefficients for prior IS studies in Appendices C and D, and for our two illustrative datasets in Appendix D. In addition, estimates of p , q , and m for future diffusion processes can be based on values computed using adoption data for earlier technologies, obtained through secondary data, event studies, or survey.

CONCLUSION

The diffusion of IS/IT innovations in different populations comprising individuals or organizations continues to be an important topic for IS research and practice. To foster greater use of TBM in IS research and practice, this study describes TBM and empirical methods, review prior IS literature on TBM, and illustrate several potential applications of TBM for IS research and practice.

Our research is subject to several limitations. First, the illustrative data sets on EC and SC technologies may be biased toward innovators in that the organizations represented on the *Information Week 500* are generally large and recognized as IT leaders who may be prone to plan, adopt, and deploy IT to a greater extent and at a quicker pace than other organizations. Second, TBM was applied to the entire population of organizations adopting a technology and to different industry groups in the larger population for illustrative purposes. Thus, the populations are interdependent although the interdependence is not explicitly modeled in the empirical models. Finally, the data used in the study are not based on a primary data collection effort and hence the quality of the data cannot be guaranteed although the *Information Week 500* surveys are influential and widely recognized.

The findings based on TBM can offer several insights for practice, especially the IS/IT vendor organizations. The innovation and imitation coefficients may be used to predict diffusion when an IS/IT innovation is about to be introduced for the first time. The results are useful to gauge the size of the potential market, the inflection point, and the peak number of adoptions. The potential market data would enable a vendor organization to determine the necessary inventory levels of the new IS/IT innovation. The inflection point and the peak number of adoptions may be used to plan the lifecycle of the IS/IT innovation including plans for the next generation of the same IS/IT innovation. The vendor organization can also use these results to determine the size or lifetime of the help desks that may be organized to foster successful diffusion of the IS/IT innovation.

Future research could examine why TBM has attracted widespread application in various disciplines other than IS. Such research could consider if IS/IT innovations are perhaps in a more embryonic stage of development or whether IS/IT innovations are systematically different from other types of innovations such as consumer durables. Alternatively, future research could examine whether the adoption processes related to IS/IT innovation are significantly different from that of other innovations. Such research could potentially shed light on whether it may be possible to treat the diffusion of IS/IT innovations synonymously with other innovations. Finally, there may be

⁴ In our study, TBM parameters are available for only two populations: EC_FIRM and SC_FIRM, and hence it is not possible to conduct data analysis using regression or structural equation models.

⁵ To illustrate this, we conducted analysis with populations defined at the level of the 2-digit NAICS industry codes. This classification resulted in 32 smaller industry groups each for EC and SC innovations. We obtained TBM parameters each population and then used p and q as dependent variables in a regression analysis that included three independent variables: initial year of adoption within the population, number of organizations in the population, and type of innovation (EC or SC). The regression results for p are significant ($R^2 = 0.424$; $F = 9.82$; $p < 0.001$) and indicate that it is positively affected by the initial year of adoption (standardized beta for the initial year of adoption = 0.64 with $p < 0.001$). The regression results for q indicate that it is not affected by any of the independent variables ($R^2 = 0.057$; $F = 0.81$ with $p = 0.50$). These findings imply that organizations in populations that adopt late encounter influence from a greater number of *other* populations whereas influence from within their own population would likely be similar regardless of the initial time of adoption.

opportunities for future research to examine if the extensions to TBM may be applicable to the study of IS/IT innovations. The insights gained from TBM analyses may be used to refine and extend the theories of the diffusion of IS/IT innovations.

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APPENDIX A

Several extensions have been proposed to overcome some of the limitations of TBM as explained in the “assumptions of the Bass model” section earlier. Table A-1 provides highlights several alternative models proposed to overcome some limitations of TBM.

Table A-1: Extensions of the Bass Model as Alternatives^a

Assumption of TBM	Summary of the alternative model	Reference
TBM produces a single value of the imitation coefficient, which describes the diffusion activity for the entire population over time.	Known as the non-uniform influence innovation diffusion model, the imitation coefficient systematically varies over time.	Easingwood, Mahajan, and Muller (1983)
TBM deals with the first purchases by potential adopters.	Building on the first-purchase non-uniform influence model (Easingwood et al. 1983), the model allows for repeat purchases.	Mahajan, Wind, and Sharma (1983)
TBM requires complete data about adoption, beginning from the inception date of the innovation.	The model describes the diffusion activity even when adoption data may not be completely available from the inception date of the innovation.	Mahajan and Peterson (1985)
TBM deals with a single generation of a product and deals with first-time adoption only and yields single values for innovation and imitation coefficients.	The model accounts for later generations of the same product that may create opportunities for new adoption as well as substitution, and may yield different values for innovation and imitation coefficients for successive generations.	Norton and Bass (1987)
TBM predicts or describes diffusion of a single innovation within a single context.	Known as the modified Bass model, the model accommodates cross-country differences in diffusion through different starting times in the various countries.	Dekimpe et al. (1998)
TBM assumes that decision variables may not be a factor for the agents involved in the diffusion process.	Known as the generalized Bass model, the model incorporates decision variables such as price. It reduces to The Bass model when the decision variables are constant over time.	Bass, Jain, and Krishnan (2000)
TBM defines a market potential, which forms the basis for prediction of the diffusion activity.	Known as the stochastic Bass model, the model allows the population size to reach infinity.	Niu (2002)
The descriptions of the alternative models provided in this section are brief due to space considerations. Readers may consult the original works for more detailed information of the alternative models.		

One alternative model allows the innovation or imitation coefficients to change over time. For example, Easingwood et al. (1983) propose the non-uniform influence innovation diffusion model, in which the imitation coefficient systematically varies over time. Mahajan et al.’s (1983) model builds on the first-purchase non-uniform influence model (Easingwood et al., 1983) by allowing repeat purchases.

Another extension deals with the problem of left-truncation or left-censoring (i.e., the data is available with cumulative number of adopters already above zero). Mahajan and Peterson (1985) suggest the following equation, wherein the data starts with time period t_0 , which may be known or not, after the last time period when the cumulative number of adopters equal to zero, and N_0 is the initial cumulative number of adopters at $t = t_0$:

$$N(t) = \left[\frac{m - \{mp(m - N_0)/(pm + qN_0)\} \exp\{-(p + q)(t - t_0)\}}{1 + \{q(m - N_0)/(pm + qN_0)\} \exp\{-(p + q)(t - t_0)\}} \right] \quad (A1)$$

Since the data is available from t_0 , $t-t_0$ in the above equation represents the time from the start of the data until any later point in time, t . Therefore, the above equation has been used (e.g., Hu et al., 1997; Wang et al., 2007) to estimate m , p , and q without knowing t_0 (i.e., the amount of time between the start of the diffusion process and the start of the data). However, using Equation 7 to address left-truncation bias can produce incorrect results because it

does not set the number of cumulative adopters at the start of the diffusion (i.e., at $t = 0$) as zero (Jiang et al., 2006). Consequently, estimation using the above equation could lead to predicted cumulative number of adopters at $t = 0$ being greater than zero. Jiang et al. (2006) propose an alternative approach, called the virtual Bass model, to indirectly address the left-truncation bias. In addition, they propose and demonstrate a more direct approach:

If the introduction time of a new product is known it is possible to obtain the adjusted parameter estimates easily by use of the direct method in which the start time of the regression is set equal to the time difference between the start of the data and the introduction time plus 1 (p. 104).

Another extension of TBM focuses on multiple generations of the product or the innovation. Norton and Bass (1987) propose a model wherein later generations of the product create new adoption opportunities and lead to substitution by adopters of prior generations. Innovation and imitation coefficients are allowed to vary across generations in this model. However, subsequent research indicates that these coefficients usually remain the same across generations (Bass, 2004).

Dekimpe et al.'s (1998) modified Bass model focused on cross-country differences in terms of the starting times for diffusion processes. Bass, Jain, and Krishan (2000) present a generalized Bass model, which incorporates decision variables (e.g., price) by adding a multiplicative term that represents their effects on the right side of Equation 1. The generalized Bass model reduces to TBM when the effect of these decision variables is stable over time. Simon and Sebastian (1987) extend TBM by arguing that advertising can affect either the innovation or imitation coefficient.

These and other extensions to TBM have been discussed in some excellent reviews (e.g., Mahajan, Muller, & Wind, 2000; Meade & Islam, 2006; Radas, 2006; Ruiz Conde, 2008).



APPENDIX B

Prior IS Studies Using the Bass Model

Study	Innovations	Adopters	Data	Constraints?	Initial values identified?	Correction for left-truncation?	Use of TBM
Loh and Venkatraman (1992)	IT outsourcing	Firms	Public announcements	None mentioned	No	No	Compared diffusion between two periods
Astebro (1995)	Electronic mail	Individuals	Tracked use of electronic mailboxes	None mentioned	No	Mahajan and Peterson's approach ^a	Compared diffusion across four departments
Tam and Hui (2001)	Mainframe computers	Firms	Secondary data	None mentioned	OLS estimates	None needed	Examined effects of price changes using extended models
Hu et al. (1997)	IT outsourcing	Firms	Public announcements	None mentioned	No	Mahajan and Peterson's approach	Compared diffusion between two periods
Dos Santos and Peffers (1998)	Automated Teller Machines	Banks	Secondary data	No ^b	Several tried	Mahajan and Peterson's approach	To understand diffusion
Shao (1999)	Expert systems	Banks	Interviews	None mentioned	No	None needed	To understand diffusion
Tam and Hui (2001)	3 ITs	Firms and individuals	Secondary data	No ^c	No	None needed	Regression using <i>m</i> as dependent variable
Teng et al. (2002)	20 ITs	Firms	Survey	None mentioned	No	None needed	Cluster analysis of ITs
Kim and Kim (2004)	17 ITs	Firms, households	Secondary data	None mentioned	No	No	Cluster analysis
Kale and Arditi (2005)	CAD	Firms	Telephone interviews	None mentioned	No	No	To understand diffusion
Florkowski and Olivas-Lujan (2006)	Human resources IT	Firms	Survey	None mentioned	No	None needed	Compared diffusion across countries and ITs
Wang et al. (2007)	Mobile internet	Individuals	Secondary data	No ^d	No	None needed	To understand diffusion
McDade et al. (2010)	39 ITs	Firms	Survey	No	No	No	To understand diffusion

^a The equation reported in the paper is similar to that suggested by Van den Bulte and Joshi (2007) but is equivalent to Mahajan and Peterson's (1985) equation reported as equation (5) in this paper by equating $N(0)$ to m_0 .
^b This paper reports negative values for p and m in the case of external-influence model, which suggests that constraints were not used.
^c This paper reports negative values for p for TBM in the case of minicomputers, which suggests that constraints were not used.
^d This paper reports negative values for p and m in the case of external-influence model, which suggests that constraints were not used.

APPENDIX C

Parameter Estimates from Prior IS Studies Using the Bass Model

Study	Period	Innovation	Adopters	p or a	q	b	M	m_0
Loh and Venkatraman (1992)	4/1988-7/1990	IT outsourcing	Firms	0.010	0.043	-	149	1.07 ^a
Astebro (1995)	1/1983-3/1988	Electronic mail	Individuals	Reports estimates of a and b for four different departments				?
Tam and Hui (2001)	1955-1984	Mainframe computers	Firms	0.007	0.121	-	2,918	0
Hu et al. (1997)	1/1985-1/1995	IT outsourcing	Firms	0.002	-	3.0×10^{-4}	190	8.95
Dos Santos and Peffers (1998)	1971-1992	Automated Teller Machines	Banks	0.008	-	1.6×10^{-6}	1.24×10^4	?
Shao (1999)	1985-1994	Expert systems	Banks	0.110	-	0.000	?	0
Tam and Hui (2001)	1965-1993	Mainframes	Firms	0.001	0.203	-	3.22×10^4	0
Tam and Hui (2001)		Mini computers	Firms	-0.002	0.247	-	3.92×10^5	0
Tam and Hui (2001)		Personal computers	Firms	0.002	0.258	-	3.12×10^6	0
Teng et al. (2002)	1951-1999	19 ITs	Firms	Reports estimates of a , b , and m for 19 different ITs ^b				
Kim and Kim (2004) ^c	1960-2003.4	17 ITs	Firms, households	0.0261	-	1.126	85.12%	?
Kim and Kim (2004)	1990-2003	CAD	Firms	0.0142	-	0.6242	193	?
Kale and Arditi (2005) ^d	1970-2003	8 human resources ITs	Firms	0.002	0.005	-	551	0
Wang et al. (2007)	Q3, 2001-Q4, 2005	Mobile internet	Individuals	0.013	-	8.5×10^{-6}	1,607	0
McDade et al. (2010) ^e	1984-?	39 ITs	Firms	0.04	0.19	-	-	?

^a Loh and Venkatraman (1992) did not use m_0 to correct for left-truncation in TBM model.

^b The inflection points differ for the 19 ITs. The estimates: a ranges from 0.0000 (for imaging) to 0.0048 (for CAD/CAM); b ranges from 0.1709 (mainframe) to 0.6863 (for LAN); and m ranges from 34.75% (for ISDN) to 100% (fixed, for EDI, email, FAX, LAN, teleconferencing, and workstation).

^c The period differs for the 17 ITs. Values for a , b , and m shown are the average values across the 17 ITs. Kim and Kim (2004) report the values for a , b , and m for each of the 17 ITs. a ranges from 1.6×10^{-13} to 0.17. b ranges from 0.15 to 2.12. m ranges from 24.1% to 100%.

^d Kale and Arditi (2005) also reported estimates of p , q , and m separately for Canadian and U.S. firms, for human resource staff and internal customers, and for 8 different types of human resources ITs.

^e McDade et al. (2010) examined 39 IT related products and only reported average values of p and q (but not m) across the 39 technologies.



APPENDIX D

Further details of the two illustrative data sets (EC_FIRM and SC_FIRM) are provided in this appendix.

We used data from the annual *Information Week 500* surveys from 1999 to 2007. These surveys are completed by chief information officers or senior IS executives from targeted firms. The 1999 survey identified a number of ITs, and asked the respondents to identify all the ITs that were being used in the organization. Moreover, for each IT the organization had adopted, the respondent was asked to identify the month and year in which it was first deployed. In subsequent years, this second question regarding the month/year of first deployment was excluded. Based on the ITs included in the surveys over the period from 1999 to 2007, we included two ITs—electronic commerce applications⁶ (EC) and electronic supply chains (SC), questions related to which were asked in 1999 and onward until 2003 and 2005, respectively.

Using the surveys from 1999 to 2003 (for EC) or 1999 to 2005 (for SC), we selected all companies for which the year of its adoption of that IT could be identified. This included any company that had either: (a) adopted the concerned IT (EC or SC) in 1999 and indicated when it had first deployed it, or (b) appeared on the *InformationWeek 500* survey in two consecutive years, not having adopted the IT in one year but having adopted it in the next year. This procedure enabled us to identify 452 companies adopting EC and 431 companies adopting SC⁷, and the year in which the company adopted EC and SC technologies. In addition, companies that reported in the last survey for each IT (2003 and 2005 for EC and SC, respectively) that they had not adopted that IT were included as non-adopters. The number of such non-adopters was 84 for EC and 157 for SC.

We identified the primary North American Industry Classification System (NAICS) classification of each adopter firm using the Lexis Nexis Academic database, and used it to classify firms into various industry groups. A company may be associated to multiple NAICS codes, but the primary NAICS code typically represents the industry from which it derives the most revenues. We used the 5-digit NAICS codes for the initial classification, but aggregated them into larger groups based on 2, 3, or 4 digit NAICS codes. Using the information on when each company adopted EC or SC, we computed the number of adopters in each year and then used the year preceding the first adoption of each IT as the starting point (i.e., $t = 0$). For each IT (EC or SC), this was done for each population (i.e., the overall sample as well as each industry).

We set M (i.e., the size of the population of adopters; Srinivasan & Mason, 1986; Van den Bulte & Lilien, 1997) for EC_FIRM and SC_FIRM to equal the population size; these firms are recognized as leaders in IT and, therefore, they could all be expected to eventually adopt both EC and SC. M was identified in this fashion for all the populations in the analysis using EC_FIRM and SC_FIRM (i.e., the overall sample and each industry group).

⁶ *InformationWeek 500* surveys from 2000 onward included an item on “electronic commerce applications”, but the 1999 survey included four relevant items (two related to customer electronic commerce and two related to business-to-business electronic commerce). These four items were combined for 1999, with the adoption of any aspects indicating adoption of EC. In the case of adoption of more than of these four aspects had been adopted in 1999, the earliest of the multiple years of first deployment was used as the year of adoption of EC.

⁷ The EC and SC adopters include 744 different companies, of which 352 organizations adopted both EC and SC.

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