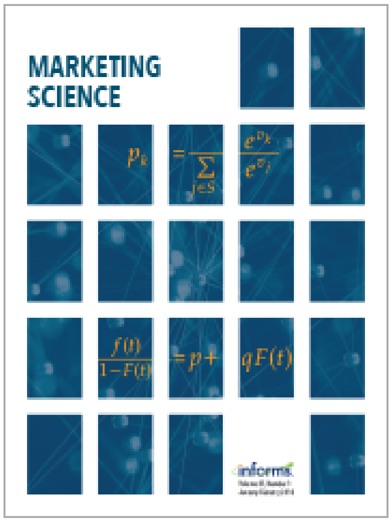

Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Multinational Diffusion Models: An Alternative Framework

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Research Note
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Abstract

The literature on cross-national diffusion models is gaining increased importance today due to the needs of present day managers. New product sales growth in a given nation or society is affected by many factors (Rogers 1995), and of these, sociocontagion (or word of mouth) has been found to be the most important factor that characterizes the diffusion process (Bass 1969, Moore 1995). Hence, it is interesting and perhaps challenging to analyze what would happen if a new product diffuses in parallel in two neighboring but culturally different countries. Not only will we expect the diffusion process in the two countries to be different, but we will also expect some interaction among them, especially if the two societies mingle with each other. There are two streams of research in cross-national diffusion. The first type focuses on exploring the differences between diffusion processes in two countries and finding out whether those differences can be attributed to social and cultural differences between the countries involved. Examples of this type of research are found in Takada and Jain (1991), Gatignon et al. (1989), Helsen et al. (1993), and Kumar et al. (1998). These studies did find some relationship between the cultural differences of the countries studied and the differences in the diffusion process. The second stream of research focuses on modeling explicitly the interaction between the diffusion processes in two countries. The interaction is typically captured through lead-lag effect (Eliashberg and Helsen 1996, Kalish et al. 1995), where the sales process in the lead country (i.e., the country where the product was first introduced) is modeled to affect the sales process in the lag country (i.e., the country where the product was introduced a few years later).

Another method to study the interaction among the diffusion processes in two countries was suggested by Putsis et al. (1997), who used a "mixing model" to empirically explore the existence of such interactions. These studies basically observed that, when a new product is introduced early in one country and with a time lag in subsequent countries, the consumers in the lag countries learn about the product from the lead country adopters, resulting in a faster diffusion rate in the lag countries. Ganesh and Kumar (1996) formulized this effect as the learning effect and, subsequently, Ganesh et al. (1997) found this learning effect to be influenced by country-specific factors (cultural similarity, economic similarity, and time lag elapsed between the lead and the lag countries) and product-specific factors (continuous vs. discontinuous innovation and the presence or absence of a standardized technology). A careful analysis of the extant literature on the second stream of research would reveal that neither the learning effect model nor the mixing model can be modified to accommodate the other model. Our contribution to the literature exactly addresses this point.

In this paper, an alternative framework is proposed that has two unique features. First, the framework is flexible enough to not only account for the lead country affecting the lag countries and vice versa, but also to accommodate the simultaneous interaction among countries in explaining the diffusion processes in the countries concerned. Using multiple product categories and a variety of new product introduction situations, we empirically demonstrate the flexibility and efficiency of our proposed framework. We found strong evidence of all types of interactions, namely, lead lag, lag lead, and simultaneous, which evidence suggests that one cannot afford to omit any of the interactions. The second unique feature of our paper is the estimation procedure that we used. Because statistical estimation of a dynamic process that includes lead-lag, lag-lead, and simultaneous types of causality within a single framework is not straightforward, we suggest an iterative estimation procedure for the estimation. This new procedure not only proved to be flexible in accommodating different types of interaction, but also converged rather quickly in all of the cases that we empirically tested. Noting that the statistical properties of these estimators are not generally available, we carried out a simulation exercise that clearly revealed the efficiency of the proposed estimation procedure. After analyzing the interaction, we went further and showed that the magnitude of the cross-national influences is affected by certain country-specific and product-specific factors. The flexibility of the proposed method over the existing methods is demonstrated through obtaining superior forecasts with the proposed method. Several interesting insights for managers concerned with formulating international marketing strategies are offered.
(*Multinational Diffusion; Iterative Estimation; Lead-Lag, Lag-Lead, and Simultaneous Effects; International Marketing Strategy*)

MARKETING SCIENCE © 2002 INFORMS
Vol. 21, No. 3, Summer 2002, pp. 318–330

0732-2399/02/2103/0318/$05.00
1526-548X electronic ISSN

Introduction

New product sales growth in a given nation or society is affected by many factors (Rogers 1995). Sociocontagion (or word-of-mouth) has been found to be the most important factor that characterizes the diffusion process (Bass 1969, Moore 1995), although latest researchers have been uncovering the role of marketing mix variables such as price (Jain and Rao 1990, Bass et al. 1994), distribution, and advertising (Horsky and Simon 1983) in the process. Noting that the socioeconomic features of a particular country basically define the diffusion of a new product, it is more interesting and perhaps challenging to analyze what would happen if a new product diffuses in parallel in two neighboring but culturally different countries. Not only will we expect the diffusion process in the two countries to be different, but we will expect some interaction among them as well, especially if the two societies mingle with each other. In such instances, understanding (1) the differences in the two diffusion processes, and (2) the interaction between those two processes are of vital importance to a multinational product manager. For example, this knowledge will help the manager better analyze two key issues—market selection, and timing and order of entry (Kumar 2000)—involved with introducing a new product in multiple countries.[1]

Through analyzing the sales data of a sample of new products in different countries, Takada and Jain (1991) showed that the differences in the diffusion rates in various countries could be attributed to some of the cultural differences between the countries and/or to the differences in the product introduction timing in those countries. In a different study, Gatignon et al. (1989) attributed the differences to country-specific factors such as cosmopolitanism, consumer mobility, and the role of women in the labor force. However, Helsen et al. (1993) could not replicate some of these results in their study. On further investigation, Kumar et al. (1998) found that the inconsistency in past research findings was due to the specific set of countries and innovations used in those different studies. It is important to note that the above-mentioned studies do not study the interaction among the diffusion processes in two countries, but simply analyze the process in each country in isolation and later compare the results from different countries on specific factors.

The interaction among the sales processes in different countries has been modeled and studied in two methods. The first method is called the lead-lag effect (Eliashberg and Helsen 1996, Kalish et al. 1995) where the sales process in the lead country (i.e., the country where the product was first introduced) was modeled to affect the sales process in the lag country (i.e., the country where the product was introduced a few years later). Ganesh and Kumar (1996) termed this phenomenon as the learning effect and, subsequently, Ganesh et al. (1997) found this learning effect to be influenced by country-specific factors (cultural similarity, economic similarity, and time lag elapsed between the lead and lag countries) and product-specific factors (continuous versus discontinuous innovation and the presence or absence of a standardized technology). The second method to study the interaction among the diffusion processes in two countries was suggested by Putsis et al. (1997), who used a "mixing model" to empirically explore the existence of such interactions. However, an empirical restriction of this model is that the focal product must have been introduced simultaneously in the two countries.

The two types of models that have been developed to study the interaction among the diffusion processes in two countries are the learning effect/lead-lag effect modeling and the simultaneous effect modeling. The former fails to address the simultaneous effect while the latter fails to address the lead-lag effect. What is more interesting is that neither model can be adapted to accommodate and/or empirically test for the presence of the other effect. Hence, if we need to accommodate both, we have to

[1]The importance of analyzing such interaction effects is best captured by Tim Bohling, Manager, Database Analytics, IBM, when he says, "It is always an issue whether to introduce the product simultaneously in all foreign markets or pick a country first and then others later. Presently, we do not have sophisticated tools to help us guide these kinds of decisions."

necessarily develop another model. But, do we need to accommodate both? Probably yes, at least in some cases. Consider this example. Videocassette recorders (VCRs) were introduced in Germany in 1974 and in Belgium and The Netherlands in 1975. Here, we can logically claim that both the lead-lag effect (Germany affecting Belgium and The Netherlands) and the simultaneous effect (Belgium and The Netherlands affecting each other) might have played a major role in the diffusion processes of the VCR in those countries. Consider another example. The Compact disk (CD) player was introduced in Belgium and Germany 1984 and in other European countries in 1985. In this instance also, there are reasons to believe in the existence of both simultaneous and lead-lag interaction effects.

There is another interesting aspect in the VCR example mentioned above. The possibility of a third effect: lag-lead effect, i.e., diffusion in Belgium or The Netherlands affecting the diffusion in Germany.

The main objective of this paper is to propose a model that can accommodate all three effects: lead-lag, lag-lead, and simultaneous effects. Putsis and Srinivasan (2000) recently summarized the following need for such a model: perhaps the most problematic criticism is the notion that there is both a sequential (i.e., lead-lag) and simultaneous nature to the diffusion process.

We empirically test our proposed model with sales data of four consumer durable innovations. In the empirical tests, we find evidence of the presence of all three effects, implying that neglect of any of the three effects will undermine the ability of an international marketing manager to understand the diffusion process in multiple countries. One can put forward many reasons for the presence of these effects. The first is that, people travel to different countries and anything new in the marketplace would more than normally attract their attention. Another reason is that, in many European and Southeast Asian countries, people in one country can watch television channels of other nearby countries, and hence, information and advertisements about a new product in one country has a high potential to be viewed by people in other countries. Finally, many sports and games involve multiple countries (Eurocup in soccer, Summer and Winter Olympics, etc.) and these events help to spread information (e.g., through advertising) about a new product across those participating countries.

The rest of the paper is organized as follows. We first develop the model, then estimate it on four consumer durables data sets and discuss the results, and finally state the various implications of the proposed framework.

Proposed Model

Our objective is to propose a model that captures the lead-lag, lag-lead, and simultaneous effects. We will develop the model in two stages: first focusing on modeling the simultaneous effect and then including the lead-lag and lag-lead effects in that model.

Consider the case where there is only simultaneous effect among the diffusion processes of a new product in two countries. To capture the effect of diffusion in one country on diffusion in the other, we model the diffusion of each country in the lines of the Generalized Bass Model (GBM) (Bass et al. 1994) as follows:

$$\frac{f(t)}{1-F_i(t)} = [p_i + q_i F_i(t)]x_i(t), \qquad i = 1, 2,$$

where $f_i(t)/(1-F_i(t))$ is the hazard function of time to adoption in country i, p_i is the coefficient of innovation or external influence, $[q_i F_i(t)]$ is the word-of-mouth effect, and $x_i(t)$ is the current marketing effort as defined in the GBM. According to the arguments of Bass et al. (1994), the current marketing effort term should include only those effects that are happening at time t because the effect of those efforts expended up to the previous time (i.e., t-1) is captured by $F_i(t)$. Because our main focus is to model the impact of diffusion in the other country (say Country 2) on this country's (say Country 1) diffusion, we model $x_1(t)$ as follows:

$$x_1(t) = 1 + (b_{21} * \text{change at time } t \text{ in diffusion force of country}_2).$$

Here, 1 represents the natural time, the diffusion force is simply the cumulative adoption up to t, and b_{21} measures the impact of Country 2's diffusion on Country 1's diffusion. Then, we have

$$x_1(t) = 1 + \left\{ b_{21} * \frac{dF_2(t)}{dt} \right\}.$$

Thus, we have the hazard function of time to adoption for Country 1 as

$$\frac{f_1(t)}{1 - F_1(t)} = [p_1 + q_1 F_1(t)] \left[1 + \left\{ b_{21} * \frac{dF_2(t)}{dt} \right\} \right]. \quad (1)$$

A similar differential equation can be derived for Country 2's diffusion. These equations can further be reduced to yield

$$F_1(t) = \frac{1 - \exp[-(p_1 + q_1)\{t + b_{21}F_2(t)\}]}{1 + \frac{q_1}{p_1} \exp[-(p_1 + q_1)\{t + b_{21}F_2(t)\}]}, \quad (2)$$

$$F_2(t) = \frac{1 - \exp[-(p_2 + q_2)\{t + b_{12}F_1(t)\}]}{1 + \frac{q_2}{p_2} \exp[-(p_2 + q_2)\{t + b_{12}F_1(t)\}]}, \quad (3)$$

where b_{21} and b_{12} represent the influences of Country 2 on Country 1, and vice versa, respectively.

The proposed model implies that diffusion in one country affects the other country's diffusion through both p and q, and that these cross-country effects are the same. This is a direct result of using the GBM. Two questions arise here. First, how does the statement that the cross-country effects act through both p and q reflect reality? Second, how valid is the assumption that these cross-country effects are the same for p and q? To answer the first question, note that consumers do get exposed to what sells in other countries through their own traveling, advertisements, newspapers such as *Wall Street Journal Europe*, etc. and, hence, it is logical to model the parameter p as affected by the other country's diffusion. Let us now look at q. Consider a potential adopter in Country 1 trying to get meaningful information from previous adopters. In our model, we claim that the degree to which a potential adopter would place faith on the internally generated information will be affected by what happens in other countries. In other words, we claim that one is likely to analyze the "locally" generated information with the information on what happens in other countries. Although there are strong reasons to believe that both p and q are likely to be affected by what happens in other countries, the impact can be different. Clearly, the best way to model is to have differential impact, one for p and another for q. However, this would make the model more complicated and not result in a closed-form solution. This is the reason for assuming a similar effect for both p and q in the proposed model. This answers the second question posed. To show that the parsimonious representation of the proposed model does not result in any major loss of information in empirical estimation, we relaxed the assumption of identical effect and empirically estimated an unconstrained model with differential effects for p and q. The results of this estimation showed that the values of the unconstrained model are similar to that of the constrained model (i.e., the proposed model) indicating no appreciable difference.[2]

We will now extend the model to include the lead-lag effect and lag-lead effect by assuming that Country 1 introduces an innovation at time t_1 and that Countries 2 and 3 introduce the same innovation in a subsequent time period t_2. Now, the diffusion process in Countries 2 and 3 can be affected by each other (simultaneous), and by Country 1 (lead-lag effect). Furthermore, the diffusion process in Country 1 can be affected by the diffusion processes in the other two countries. Applying a similar modeling logic discussed in the simultaneous case, it can be shown that

$$\begin{aligned} F_1(t) &= \frac{1 - \exp[-(p_1 + q_1)t]}{1 + \frac{q_1}{p_1} \exp[-(p_1 + q_1)t]} \quad \forall t_1 \leqslant t \leqslant t_2 \\ &= \frac{1 - \exp[-(p_1 + q_1)\{t + b_{21}F_2(t) + b_{31}F_3(t)\}]}{1 + \frac{q_1}{p_1} \exp[-(p_1 + q_1)\{t + b_{21}F_2(t) + b_{31}F_3(t)\}]} \\ &\quad \forall t \geqslant t_2, \end{aligned} \quad (4)$$

[2]We thank a reviewer for suggesting this. In fact, the unconstrained model with differential impact resulted in estimates with higher standard errors, suggesting that the parsimony of the proposed model enables us to obtain more reliable estimates. Results can be obtained from the authors upon request.

$$F_2(t) = \frac{1 - \exp[-(p_2 + q_2)\{t + b_{12}F_1(t) + b_{32}F_3(t)\}]}{1 + \frac{q_2}{p_2}\exp[-(p_2 + q_2)\{t + b_{12}F_1(t) + b_{32}F_3(t)\}]} \quad \forall t \geqslant t_2, \tag{5}$$

$$F_3(t) = \frac{1 - \exp[-(p_3 + q_3)\{t + b_{13}F_1(t) + b_{23}F_2(t)\}]}{1 + \frac{q_3}{p_3}\exp[-(p_3 + q_3)\{t + b_{13}F_1(t) + b_{23}F_2(t)\}]} \quad \forall t \geqslant t_2. \tag{6}$$

Note that the coefficients b_{32} in Equation (5) and b_{23} in Equation (6) pertain to the simultaneous impact Countries 2 and 3 have on each other, the coefficients b_{12} in Equation (5) and b_{13} in Equation (6) pertain to the lead-lag effect the lead Country 1 has on the lag Countries 2 and 3, and the coefficients b_{21} and b_{31} in Equation (4) pertain to the lag-lead effect that the two Countries 2 and 3 have on the lead Country 1's diffusion.[3] Thus, we have a framework that accommodates all three effects, namely, the lead-lag effect, lag-lead effect, and simultaneous effect. The proposed model is, in essence, an extension of the GBM that seems to successfully accommodate the various interaction effects that typically characterize the diffusion of a new product in multiple countries.

Why We Do Need an Alternative Model?

To answer this, we will compare the proposed model with the learning (i.e., lead-lag effect) model developed by Ganesh and Kumar (1996) and Kalish et al. (1995) and the mixing model (i.e., simultaneous effect) by Putsis et al. (1997) that are reproduced here.

Learning model:

$$\frac{f_1(t)}{(1 - F_1(t))} = (p + q \cdot F_1(t) + C \cdot F_2(t)),$$

Mixing model:

$$\frac{f_1(t)}{(1 - F_1(t))} = (a_1 + c_1 \cdot (\rho) \cdot F_1(t) + c_2 \cdot (1 - (\rho) \cdot F_2(t)),$$

Proposed model:

$$\frac{f_1(t)}{(1 - F_1(t))} = (p + q \cdot F_1(t))\left(1 + b_{21} * \frac{dF_2(t)}{dt}\right).$$

As mentioned earlier, while the learning model and the mixing model can accommodate only one of the two effects, namely, lead-lag and simultaneous effects, respectively, but not both, the proposed model accommodates both. However, it should be noted that the mixing model (Putsis et al. 1997) does allow theoretically for all of the effects, but the empirical estimation of effects other than the simultaneous effect does not appear to be possible using an unbalanced data set. Second, the proposed model can accommodate the lag-lead effect, which cannot be accommodated by either the learning model or the mixing model. Finally, only the proposed model provides a closed-form solution, which is useful not only for better forecasting but also for carrying out "what if" analyses.

Before we proceed further with an empirical estimation of our proposed model, it has to be mentioned here that as suggested by DeKimpe et al. (2000), our model overlooks another important aspect of multinational diffusion, namely, the two-stage nature of the multimarket diffusion process. The first stage refers to the adoption time *across* the different markets, and the second stage refers to the adoption pattern *within* each of those markets. Clearly, these two are interrelated. By focusing on the second stage alone, we, in this proposed model, are abstracting away from the implications of the first stage. However, the various cross-country effects that we model in the proposed framework will, to some extent, account for the implications of the first stage (DeKimpe et al. 2000).

[3]It should be noted that lead-lag effects and lag-lead effects are so named to indicate the mutual impact that the lead and the lag countries have on each other. In principle, this is the same as the simultaneous impact that the countries have on each other. However, the difference between the two will be more prominent when the introduction time difference between the two countries is large. We thank a reviewer for pointing this to us.

Empirical Demonstration

The objective of this section is to demonstrate how versatile the proposed model is in accommodating different types of interactions between the diffusion processes of different countries. To achieve this objective, we fitted the model to the sales data of four consumer durables obtained from different countries in Europe. The diffusion patterns of microwave ovens, home computers, CD players, and cellular phones were analyzed for six European countries (the actual number of countries used varied with product category and availability of reliable data). The countries include Belgium, Germany, the United Kingdom, France, Denmark, Finland, and Norway.

Data

The data required for modeling the diffusion process in this study were yearly sales data for each product in all countries studied. The data were collected from the first year of introduction of the product in each of the countries through the time period for which the most recent data were available (Euromonitor Publications 1984–1999). Data were available until 1997 for all product categories and the countries included in this study. Also, the country in which a product was first introduced in the region (Europe) was categorized as the lead country for that product category. For example, in the case of microwave ovens data were collected for Germany from 1974 to 1997 (1974 being the year that the product was first introduced in Germany). Similarly, data on the sales of microwave ovens were collected for the United Kingdom from 1975 to 1997 and for France and Denmark from 1976 to 1997.

In the case of CD players, data were chosen for two countries and were available from the first year (1984) of introduction to 1997. Both countries introduced the innovation simultaneously. In the case of home computers, two countries (the United Kingdom and Germany) were chosen for the analysis. Also, for this category, the United Kingdom was the country where the product was first introduced in 1980 and, hence, was categorized as the lead country. Germany is the lag country since the product was introduced in 1981. Finally, for the cellular phone category, data were available for three countries, with Norway being the lead country where the innovation was first introduced in 1981. Denmark and Finland introduced cellular phones a year later in 1982. For cellular phones the unit sales data were also made available by a leading manufacturer of the product in Europe and were used in the estimation of the models. For all categories, the estimation sample comprised annual sales data for all countries until 1991, and the holdout sample comprised sales data from 1992 to 1997(which were used for evaluating the predictive accuracy of the proposed framework vis-à-vis other models used in the literature).

Model Estimation

Although the proposed diffusion framework is flexible enough to include all three effects, estimating the model poses a challenge because of the existence of the simultaneous cause-effect relationship between diffusions in two countries. Fortunately, we do have closed-form expressions for the demand functions, where the sales of each country are expressed as a function of only one variable, time. We will make use of the closed-form solutions shown below for estimation. The simultaneous impact between diffusion processes in two countries is captured by

$$F_1(t) = \frac{1-\exp[-(p_1+q_1)\{t+b_{21}F_2(t)\}]}{1+\frac{q_1}{p_1}\exp[-(p_1+q_1)\{t+b_{21}F_2(t)\}]}, \quad (7)$$

$$F_2(t) = \frac{1-\exp[-(p_2+q_2)\{t+b_{12}F_1(t)\}]}{1+\frac{q_2}{p_2}\exp[-(p_2+q_2)\{t+b_{12}F_1(t)\}]}. \quad (8)$$

Consider Country 1. Note that the sales function

$S_1(t)$ = function ($F_1(t)$; m_1), where $F_1(t)$ = function ($F_2(t)$, t; p_1, q_1, b_{21}), where $F_2(t)$ = function ($F_1(t)$, t; p_2, q_2, b_{12}), and so on.

Thus, we find that Country 1's sales growth is a recursive function and the parameters involved are p_1, q_1, p_2, q_2, b_{12}, b_{21}, and m_1. However, it does not explicitly depend on any variable other than t. Specifically, it is not stated as a function of Country 2's actual sales or cumulative sales. Similarly the sales function

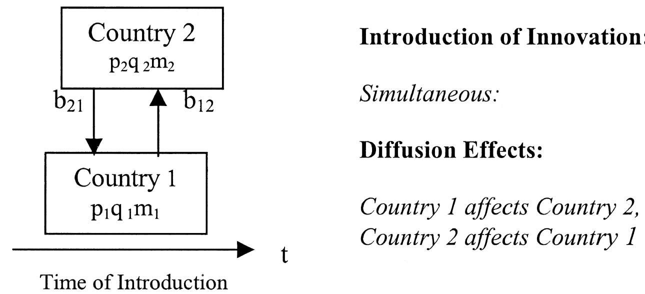
$S_2(t)$ = function ($F_2(t)$; m_2), where $F_2(t)$ = function ($F_1(t)$, t; p_2, q_2, b_{12}), where $F_1(t)$ = function ($F_2(t)$, t; p_1, q_1, b_{21}), and so on.

This implies that Country 2's sales growth is a recursive function of t alone and not of Country 1's actual sales or cumulative sales.

Hence, we can actually estimate each country's recursive sales equation separately. However, because they share some of the parameters, we estimate the two equations together. A common technique applied for all recursive equations is to start from somewhere and proceed iteratively until some convergence criterion is met (Johnston 1984, pp. 467–469, Seber and Wild 1989). We adopt the same technique here. Initially assume $F_2(t) = 0$ on the right-hand side of the $S_1(t)$ equation and $F_1(t) = 0$ on the right-hand side of the $S_2(t)$ equation. The estimation of these initial sets of equations will yield the initial estimates of p_1, q_1, p_2, and q_2, which, then, can be used to obtain first-cut predicted values for $F_2(t)$ and $F_1(t)$ to be used on the right-hand sides of equations $S_1(t)$ and $S_2(t)$, respectively. This, then, is used to reestimate the equations, which will yield a new set of estimates for p_1, q_1, p_2, q_2, b_{12}, and b_{21} that are again used to repredict the values for $F_2(t)$ and $F_1(t)$. This iterative procedure is continued until convergence is obtained and is explained in detail in Appendix A.

The suggested estimation procedure looks similar to the 2SLS (two-stage least squares) procedure or the 3SLS procedure, but there is a difference. In these procedures, the dependent variables appearing on the right-hand sides of a set of simultaneous equations are *observed* while in our case they are not. Hence, we have to resort to the estimation technique explained above. We wrote the program using a SYStem of NonLINear equations (SYSLIN) in statistical analysis software (SAS) to do this iterative procedure. We were able to obtain convergence within 9 to 10 iterations for all cases involved. However, because the statistical properties of such estimators are not established, we conduct simulation to better understand the basic properties of the estimators. In Appendix B, we provide the description of and results from the simulation exercise. As can be seen from the results shown in Appendix B, the overall means of the estimates of all eight parameters in the model are quite close to the simulated values. The low values for the standard deviation also indicate the tightness of the distribution of the parameter values. In other words, the proposed iterative estimation procedure does accurately capture the simulated parameters.

Figure 1 **Case 1: Simultaneous Effects**



Discussion of Results

The results of the analysis are discussed in this section for a variety of cases. The reader can refer to Figures 1 through 4 to understand the various interaction effects that we use in the discussion. Each of the figures corresponds to each of the four cases discussed in this study.

Case 1. The model is shown in Figure 1 and the results of the iterative estimation are presented in Table 1. The product concerned is CD player. Germany and Belgium simultaneously introduced CD players in 1984 and data used for estimation of the proposed model were available up to 1997. Because we have two countries that had the introduction in the same time period, the model recovered only the simultaneous effects.

The external p and the internal q coefficients are 0.013 and 0.43 for Belgium, and 0.01 and 0.49 for Germany, respectively. These parameters are significant at $\alpha = 0.05$. The market potential values are estimated to be 0.519 million and 14.96 million for

Table 1 Case 1 (Product Category: CD Players)

Country	Year of Introduction	External p	Internal q	Market Potential m (000s)	Simultaneous Interaction Effect
Belgium (1)	1984	0.013	0.43	519	0.009 (b_{21})
Germany (2)	1984	0.01	0.49	14,960	0.003 (b_{12})

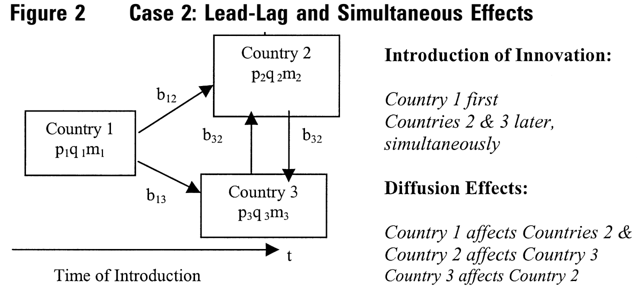
All coefficients are significant at $\alpha = 0.05$ unless otherwise indicated.

Belgium and Germany, respectively. The estimated coefficients exhibit face validity in terms of its magnitude and direction. The simultaneous interaction parameters b_{12} and b_{21} are significant at $\alpha = 0.05$. The effect of Germany on Belgium is estimated to be 0.009 (b_{12}) and the effect of Belgium on Germany is found to be 0.003. Higher influence from Germany to Belgium than vice versa is probably due to the common perception that Germany is the most technologically advanced country in Europe.

Case 2. This model is shown in Figure 2 and the results of the estimation are given in Table 2. The product concerned is cellular phones. Norway introduced cellular phones in 1981 and is considered the lead country. Denmark and Finland introduced them a year later in 1982. For cellular phones, the unit sales data were made available by a leading manufacturer of the product in Europe and were used in the estimation. The interesting result is that when the proposed model was fitted to these data sets, we found that the lead-lag and simultaneous effects were significant. The lag-lead effect was not found to be significant.

The external and internal coefficients are 0.021 and 0.20 for Norway, 0.014 and 0.25 for Denmark, and 0.005 and 0.33 for Finland, respectively. The estimated market potential values reflect reality to a large extent (i.e., the total number of adopters relative to the total population). The simultaneous influence between Finland and Denmark is positive and significant, with Finland's influence over Denmark being 0.004 (b_{23}) and Denmark's influence on Finland being 0.007 (b_{23}). It can be seen that Norway has a greater lead-lag impact on Finland (b_{13} = 0.009) than over Denmark (b_{12} = 0.006). This is understandable, given the similarities (on a relative basis) between Norway and Finland. As mentioned earlier, neither of the two lag countries, namely, Denmark and Finland, had any effect on the diffusion of the lead country of Norway.

Figure 2 Case 2: Lead-Lag and Simultaneous Effects



Case 3. The model is presented in Figure 3 and the results of the iterative estimation are presented in

Table 2 Case 2 (Product Category: Cellular Phones)

Country	Year of Introduction	External p	Internal q	Market Potential m (000s)	Interaction Effect: Lead-Lag from Country 1	Interaction Effect: Simultaneous
Norway (1)	1981	0.021	0.20	509		
Denmark (2)	1982	0.014	0.25	431	0.006(b_{12})	0.004(b_{32})
Finland (3)	1982	0.005	0.33	618	0.009(b_{13})	0.007(b_{23})

All coefficients are significant at $\alpha = 0.05$ unless otherwise indicated.

Table 3 Case 3 (Product Category: Microwave Ovens)

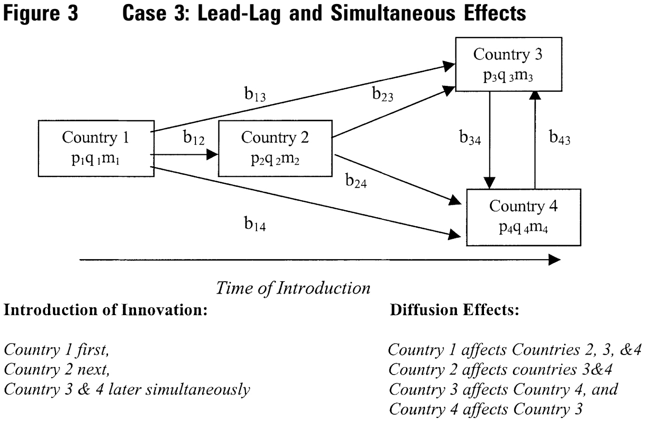
Country	Year of Introduction	External p	Internal q	Market Potential m (000s)	Interaction Effect: Lead-Lag from Country 1	Interaction Effect: Lead-Lag from Country 2	Interaction Effect: Simultaneous
Germany (1)	1974	0.0006	0.38	33,618			
United Kingdom (2)	1975	0.003	0.49	17,961	0.007 (b_{12})		
France (3)	1976	0.0005	0.61	12,644	0.009 (b_{13})	0.005 (b_{23})	0.002 (b_{43})
Denmark (4)	1976	0.002	0.50	596	0.007 (b_{14})	0.003 (b_{24})	0.004 (b_{34})

All coefficients are significant at $\alpha = 0.05$ unless otherwise indicated.

Table 3. The product concerned is the microwave oven. Germany introduced the microwave oven in 1974 followed by the United Kingdom in 1975, and France and Denmark in 1976. When the proposed model was estimated on these data sets, we found a significant lead-lag effect of Germany on all three countries, namely, the United Kingdom, France, and Denmark, a significant lead-lag effect of the United Kingdom on France and Denmark, and a significant simultaneous effect of France and Denmark on each other. Here again, we did not find any evidence of lag-lead effect, i.e., lag countries affecting the lead countries.

The external and internal coefficients are 0.0006 and 0.38 for Germany compared to 0.003 and 0.49 for the United Kingdom, 0.0005 and 0.61 for France, and 0.002 and 0.50 for Denmark. The effect of the lead country, Germany, on the lag country, United Kingdom, is significant and positive ($b_{12} = 0.007$). Similarly, lead-lag effects ($b_{13} = 0.009$ and $b_{14} = 0.007$) are observed for other lag countries. An interesting observation here is that the second country, the United Kingdom, also has a significant and positive influence on subsequent lag countries on France ($b_{23} = 0.005$) and on Denmark ($b_{24} = 0.003$). Finally, the simultaneous effect between France and Denmark is significant and positive in both directions. The effect of France on Denmark ($b_{34} = 0.004$) is, however, greater than the effect of Denmark on France ($b_{34} = 0.002$). This differential effect is also intuitive, given that France is a larger country, is much more technologically advanced, and has been one of the leaders in the European region. As mentioned earlier, the lag-lead effect was absent.

Figure 3 Case 3: Lead-Lag and Simultaneous Effects



Case 4. The model and the results of the estimation are presented in Table 4. The product concerned is the home computer. The United Kingdom first introduced home computers in 1980 and is, therefore, termed as the lead country. Germany introduced the same innovation a year later in 1981. When the proposed model was estimated on these data sets, we found significant lead-lag (i.e., the United Kingdom

Figure 4 Case 4: Lead-Lag and Lag-Lead Effects

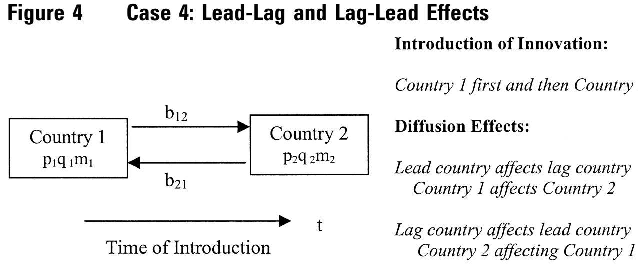


Table 4 Case 4 (Product Category: Home Computers)

Country	Year of Introduction	External p	Internal q	Market Potential m (000s)	Lead-Lag from Country 1	Lag-Lead from Country 2
United Kingdom (1)	1980	0.026	0.29	16,780	–	0.003 (b_{21})
Germany (2)	1981	0.011	0.36	22,460	0.007 (b_{12})	–

All coefficients are significant at $\alpha = 0.05$ unless otherwise indicated.

on Germany) and lag-lead effects (i.e., Germany on the United Kingdom) as well.

The external and internal coefficients are 0.026 and 0.29 for the United Kingdom and 0.011 and 0.36 for Germany, respectively. The market potential values of about 17 million and 22.5 million for the United Kingdom and Germany reflect the size of the country. Regarding the interaction effects, the lead-lag effect ($b_{12} = 0.007$) is greater than the lag-lead effect ($b_{21} = 0.003$). Both of these effects are significant at $\alpha = 0.05$. The findings suggest that probably the pioneers seem to have a stronger influence on the followers than vice versa.

From the empirical demonstration, it can be noted that:

- The proposed model is versatile enough to help a manager efficiently uncover various interaction effects between the diffusion processes in multiple countries.
- It is informative to note that while the lead-lag effects estimated with the proposed model range from 0.002 to 0.009, the estimates of this effect were found to be in a higher range (0.01 to 0.10) when we used these data sets to estimate the learning model used by Ganesh and Kumar (1996) and Ganesh et al. (1997).

What Do the Interaction Effects Mean?

Ganesh et al. (1997) found that the lead-lag effect (in their learning effect model) was influenced by country-specific factors (cultural similarity, economic similarity, and time lag elapsed between the lead and the lag countries) and product-specific factors (continuous vs. discontinuous innovation and the presence or absence of a standardized technology). Can we say something similar about the interaction parameters estimated on the proposed model in the four cases?

To assess the reasons for differences in the magnitude of the interaction coefficients (i.e., b_{ij} coefficients) we regressed the b_{ij}'s from all four cases as a function of certain country-specific and product-specific factors. The country-specific factors include cultural similarity and economic similarity measures. The measures for cultural similarity were drawn from Hofstede (1980)—power distance, individualism, masculinity/feminity, and uncertainty avoidance. These four dimensions were hypothesized to constitute fundamental value orientation that underlies national differences in management practices, organizational pattern, and decision making. Cultural similarity is measured as a negative index of the sum of absolute differences in each of the four Hofstede (1980) dimensions, between the corresponding pair of countries. Similarly, economic similarity is operationalized as a negative index of the sum of absolute differences in the standardized values (given the differences in the unit of measurement) of gross domestic product (GDP) per capita, level of urbanization, and unemployment rate between the corresponding pair of countries. The product-specific factor, represented by the type of innovation, is operationalized as a dummy variable with a value of 1 for continuous innovation and 0 otherwise. The expectation is that consumers already have some knowledge regarding the core benefits of the continuous innovation and, therefore, the cross-national diffusion impact (i.e., the interactions effect) should be higher.

The results from the model estimation yield values (significant at $\alpha = 0.05$) of 0.14 and 0.09 for cultural and economic similarity, and 0.18 for the type of innovation. It can be seen that the interaction coefficients estimated on the four cases using the proposed model do depend, to a large extent, on the country-specific and product-specific factors. Finally, the predictive accuracy of the proposed model when estimated on the holdout sample is much better than those of the learning and mixing model. This adds further credence to the proposed framework.

Implications, Conclusions, and Limitations

In this paper, we propose a framework to estimate three types of effects that can exist in a multinational diffusion setting: lead lag, lag lead, and simultaneous. The empirical illustrations support the presence of those systematic effects. The cross-national diffusion effects captured in the proposed framework across multiple product categories have implications for managers in their decision-making process. If the lead-lag effect is observed consistently between a pair of countries, then, for a new innovation the order of entry into those two countries is such that the product is first introduced in the lead country and then into the lag country (i.e., waterfall strategy). If there is no lead-lag effect but only simultaneous effects present for a set of countries, then, for a new innovation, the product can be simultaneously introduced in those countries (i.e., the Sprinkler strategy). If lag-lead effects are also present, then, also the order of product introduction into those countries is set. Thus, the proposed framework can be a useful input among other factors for foreign market entry decisions.

The proposed framework can also be used to examine the diffusion process at the segment level within a country. For example, cellular phones were introduced to attract the segment that considered "convenience" and "business use" to be of utmost importance. Subsequently, many other segments that considered "security," "personal use," and so forth started using cellular phones. Therefore, one can link the diffusion process in one segment to other segments to understand the lead-lag, lag-lead, and simultaneous interaction among segments. Similarly, if there are multiple brands in the marketplace, then, one can study the influence of one brand's diffusion process on the other brands. For example, in many markets, two brands of wireless phones entered the market. Subsequently, four other brands entered the market in different time periods. As later brands entered the market, some of the former brands lost market share. This indicates that brands do affect one another. Thus, it is worthwhile to study how the diffusion process of one brand affects other brands (Krishnan et al. 2000). This can benefit brand managers because more accurate sales forecasts for their respective brands can be generated.

The findings of this study are based on consumer durables and, therefore, may not generalize to industrial technological innovations. Also, the scope of the present study is limited due to the problems associated with the reliability and availability of time series data across multiple countries. Also, the definitions of products (e.g., home computers) may not be consistent across countries. This study examines diffusion patterns only in European countries (predominantly developed economies) and as such the findings cannot be generalized to other developing and less developed economies. Future research can focus on systematically capturing all possible effects across countries to better understand the influence between continents and different types of innovations.

Acknowledgments

The author(s) thank the editor, the area editor, the reviewers, Frank Bass, Erin Anderson, David Midgely, Vijay Mahajan, Ed Blair, Rajkumar Venkatesan, Anish Nagpal, Werner Reinartz, the participants at the 1999 Marketing Science Conference, INSEAD Research Seminar, University of Maryland Research Seminar, and the FGV Business School in Brazil. This

Table 5 Parameters Recovery from Simulated Data Sets

Parameters	Actual	Simulated Data	
		Mean*	Standard Deviation
p_1	0.003	0.00257	0.00049
q_1	0.29	0.28253	0.03492
m_1	1,230	1,254.74	30.231
b_{12}	0.003	0.00310	0.00106
p_2	0.002	0.00179	0.00007
q_2	0.39	0.39031	0.00415
M_2	2,800	2,821.37	75.493
b_{21}	0.002	0.00194	0.00023

*The mean values are based on 300 data sets.

research was partially supported by the Small Grants Program at the University of Houston.

Appendix A
Estimation of the Proposed Model

We estimate the recursive set of Equations (7) and (8) as follows:

Step 1. Assign a value of 0 to $F_1(t)$ and $F_2(t)$ on the right-hand side of Equations (7) and (8).

Step 2. Estimate p_1, q_1, p_2, and q_2 of the two resulting equations. Call them $(p_1, q_1, p_2, q_2)_0$.

Step 3. Using $(p_1, q_1, p_2, q_2)_0$ and using 0 for F_1 and F_2 on the right-hand sides, evaluate $F_1(t)$ and $F_2(t)$ of Equations (7) and (8). Call these $\{F_1(t), F_2(t)\}_1$.

Step 4. Assign $\{F_1(t), F_2(t)\}$ to the $F_1(t)$ and $F_2(t)$ on the right-hand side of Equations (7) and (8) and estimate p_1, q_1, b_{21}, p_2, q_2, b_{12} of the two resulting equations. Call them $(p_1, q_1, b_{21}, p_2, q_2, b_{12})_1$.

Step 5. Using $(p_1, q_1, b_{21}, p_2, q_2, b_{12})_1$ and using $\{F_1(t), F_2(t)\}_1$ for $F_1(t)$ and $F_2(t)$ on the right-hand sides, evaluate $F_1(t)$ and $F_2(t)$ of Equations (7) and (8). Call these $\{F_1(t), F_2(t)\}_2$.

Step 6. Assign $\{F_1(t), F_2(t)\}_2$ to $F_1(t)$ and $F_2(t)$ on the right-hand side of Equations (7) and (8) and estimate p_1, q_1, b_{21}, p_2, q_2, b_{12} of the two resulting equations. Call them $(p_1, q_1, b_{21}, p_2, q_2, b_{12})_2$.

Repeat Steps 5 and 6 until you find no discernible changes[4] in the estimates of p_1, q_1, b_{21}, p_2, q_2, b_{12}.

[4]One can use any logically appropriate stopping point. As noted by a reviewer, the important point to note is that the changes should be decreasing at such a rate that the convergence is achieved and that the estimates do not blow up or keep oscillating. In all of the cases that we examined, we did get convergence. Our stopping criterion was getting no more changes in the fifth decimal place of the estimate.

Appendix B
Data Simulation and Recovery of Parameters Using the Proposed Iterative Estimation Procedure

To better understand the efficiency of the proposed estimation method, we simulated data assuming certain parameter values. We assumed values for p_1, q_1, b_{12}, p_2, q_2, b_{21}, m_1, and m_2, and using Equations (7) and (8), we generated values for $F_1(t)$ and $F_2(t)$. Then we used the following equation to generate the diffusion data:

$$S(t) = m[F(t) - F(t-1)]$$

where, $S(t)$, $F(t)$, and m are as defined before.

We generated annual sales data. We chose $p_1 = 0.003$, $q_1 = 0.29$, $b_{12} = 0.003$, $m_1 = 1{,}230$, $p_2 = 0.002$, $q_2 = 0.39$, $b_{21} = 0.002$, $m_2 = 2{,}800$ and generated data for the time periods $t = 1$ to $t = 14$. The choice of the values for the parameters in the simulation reflects the values that we observed in the analysis of the actual data sets. To the sales data, we then multiplicatively added symmetric normal error at 3 different levels of variance: 0.05, 0.1, and 0.2. We then used Monte Carlo simulation to generate 100 different data sets.

The errors were included in the data set multiplicatively as $S'(t) = S(t) \times (1 + \varepsilon)$. This procedure for including errors proportionate to the dependent variable in nonlinear models for Monte Carlo simulation purposes is a common practice in econometrics. Further, with respect to generating the data using Monte Carlo simulation, Kennedy (1998) says that "... if the variance of the error varies from observation to observation, depending on the value of the independent variable, then the error terms must be adjusted accordingly..." Because we have a strong reason to believe that the error term is likely to have a higher variance at higher values of the sales, we follow Kennedy (1998) in using the proportional error term.

The next issue is the degree of randomness to be introduced in the generated data sets. A normal error with a standard deviation of 0.1 introduces enough noise in the data set, more than what we usually see in a typical diffusion data set. However, to be sure, we checked with 3 values of error variances (0.05, 0.1, and 0.2). Because, data were generated for two countries here, we developed three simulation scenarios. The error was introduced to Country 1 in Scenario I, Country 2 in Scenario II, and to Countries 1 and 2 in Scenario III. Thus, 100 different data sets were generated for each of these scenarios.

The results reported represent the average values across all 300 data sets. In Scenario III, where error is introduced to Countries 1 and 2, the sum of the error variance in both countries did not exceed the set values (0.05, 0.1, and 0.2). Different starting values were used each time to evaluate whether the convergence obtained is local or global.

The results in Table 5 clearly indicate that irrespective of the starting values for the parameters, the overall means for all eight parameters are quite close to the simulated values. The low values for the standard deviation also indicate the tightness of the distribution of the parameter values. In other words, the proposed iterative estimation procedure does accurately capture the simulated parameters. To test the efficiency of the estimation procedure across other cases, we generated data for each of the three remaining cases. As the number of countries increases, the number of the data sets generated also increases. However, the simulation results were quite similar to those presented above. The robustness of the proposed estimation procedure is thus evident.

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This paper was received July 14, 2000, and was with the authors 11 months for 4 revisions; processed by Gary Lilien.