Investigating New Product Diffusion Across Products and Countries

Debabrata Talukdar • K. Sudhir • Andrew Ainslie
School of Management, SUNY at Buffalo, Buffalo, New York 14260
School of Management, Yale University, New Haven, Connecticut 06520
The Anderson School at UCLA, Los Angeles, California 90095
dtalukda@acsu.buffalo.edu • sk389@mail.som.yale.edu • andrew.ainslie@anderson.ucla.edu

Abstract

As firms jockey to position themselves in emerging markets, firms need to evaluate the relative attractiveness of market expansion in different countries. Since the attractiveness of a market is a function of the eventual market potential and the speed at which the product diffuses through the market, a better understanding of the determinants of market potential and diffusion speed across different countries is of particular relevance to firms deliberating their market expansion strategies. Despite a recent spurt in research on multinational diffusion, there exist significant gaps in the literature. First, existing studies tend to limit their analysis to industrialized countries, thus reducing the ability to generalize the insights to many emerging markets. Second, these studies tend to focus on the coefficients of external and internal influence in the Bass diffusion model but do not analyze the determinants of market potential. Third, the choice of variables that affect the parameters of the Bass diffusion model has been rather limited.

In this paper, we seek to address these gaps in the literature. To address the scope issue, we assembled a novel dataset that captures the diffusion of 6 products in 31 developed and developing countries from Europe, Asia, and North and South America. The set of countries in our dataset encompasses 60% of the world population and includes such emerging economies as China, India, Brazil, and Thailand. This should provide us with a stronger basis to make empirical generalizations about the diffusion process.

For firms seeking to expand into emerging international markets, our findings about penetration potential have considerable significance. For example, we find that for the set of products that we analyze the average penetration potential for developing countries is about one-third (0.17 versus 0.52) of that for developed countries. We also find that it takes developing countries on average 17.9% (19.25 versus 16.33 years) longer to achieve peak sales. Thus, despite the well-known positive effect of product introduction delays on diffusion speed, we find that developing countries still continue to experience a slower adoption rate, compared to that of developed countries.

Our study also investigated the impact of several new macroenvironmental variables on penetration potential and speed. For example, our findings indicate that a 1% change in international trade or urbanization level can potentially change the penetration potential by about 0.5% and 0.2% respectively. These are some of the key variables projected to change significantly over the coming years for developing countries. While business managers have relatively little influence on such variables, our findings can still serve as a valuable empirical guide for the variables that they should consider in evaluating diverse international markets and in performing sensitivity analysis with respect to their projected trends.

Finally, our study also holds implications for managers seeking to combine information about past diffusion patterns across products and countries for better prediction. We pool information efficiently across multiple products and countries using a Hierarchical Bayes estimation methodology. By sharing information across countries and products in a single, coherent framework, we find that this pooling approach leads to substantial improvements in prediction accuracy. Our technique is particularly superior in predicting sales and BDM parameter values in the early years of a new product introduction in a new country, when forecast estimates are managerially most useful. We also decompose the variance in the BDM model parameters into product, country, and product-country components. These results give guidelines to managers about which market experience they should weigh more to arrive at forecasts of market potential and diffusion speed. We find that while past experiences of other products in a country (country effects) are relatively more useful to explain penetration level (cumulative sales), past experiences in other countries where a product was earlier introduced (product effects) are more useful to explain the coefficients of external and internal influence (and thus the speed with which the product will attain peak sales).

(*Diffusion; International Marketing; Hierarchical Bayes; Forecasting*)

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1. Introduction

Global marketing has become more important than ever with the rapid and continuing economic expansion in many major developing countries such as China, India, and Brazil (Whelan 2000). As firms jockey to position themselves in such emerging markets, managers need to evaluate the relative attractiveness of market expansion in different countries. Since the attractiveness of a market is a function of the eventual market potential and the speed at which the product diffuses through the market, a better understanding of the determinants of market potential and diffusion speed across different countries is of particular relevance to firms deliberating their market expansion strategies.

The *Bass Diffusion Model* (BDM) (Bass 1969) has been widely used as a descriptive model of the product diffusion process in marketing. The increasing importance of global marketing has given rise to a spurt of research that investigates multinational diffusion (Gatignon et al. 1989, Takada and Jain 1991, Helsen et al. 1993, Putsis et al. 1997, Kumar et al. 1998, Dekimpe et al. 2000a, b). Nevertheless, there exist significant gaps in the literature (Mahajan et al. 2000).

First, existing studies tend to limit their analysis to industrialized countries, thus reducing the ability to generalize the insights to many emerging markets. For example, Dekimpe et al. (2000a) note that the set of countries considered in these existing studies is ''not only limited in scope, but also severely biased towards the study of *industrialized* countries. . . . Little is known, however, about the nature of the diffusion process in developing countries.'' Second, these studies tend to focus on the coefficients of external and internal influence in the BDM, but do not analyze the determinants of market potential. Third, the choice of variables that affect the parameters of the BDM has been rather limited (Huszagh et al. 1992, Putsis et al. 1997).

In this paper, we seek to address these gaps in the literature. To address the scope issue, we assembled a novel dataset that captures the diffusion of 6 products in 31 developed and developing countries from Europe, Asia, and North and South America. The set of countries in our dataset encompasses 60% of the world population and includes such emerging economies as China, India, Brazil, and Thailand. This should provide us with a stronger basis to make empirical generalizations about the diffusion process.

We also investigate the impact of a much larger set of covariates on the diffusion process than any other single international diffusion study. The geographic scope of our data allows us to test whether the earlier findings about the role of some of these covariates generalize from developed to developing country contexts. To the best of our knowledge, we study the role of several macroenvironmental variables for the first time in the marketing literature. This is particularly true with regard to our analysis of product penetration potential, which is a key measure for evaluating attractiveness of international markets. For example, how do differences in international trade participation or urbanization level affect penetration potential? How do differences in economic stratification of consumers impact the communication process by which consumers learn about the innovation?

Finally, we show that by combining information about past diffusion patterns across products and countries we can improve the predictive power of the BDM. A major criticism of single countrysingle product models is that ''parameter estimation for diffusion models is basically of historical interest: By the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes'' (Mahajan et al. 1990, p. 9). We build on the tradition of Gatignon et al. (1989) and Dekimpe et al. (1998) (who combine information about a particular product's diffusion across countries) and Lenk and Rao (1990) (who combine information across multiple products' diffusion within one country) by combining information across countries and products in a single, coherent framework using a Hierarchical Bayes (HB) estimation procedure. Putsis and Srinivasan (2000), in their review of estimation techniques for diffusion models, note: ''Approaches such as the HB approach . . . are in our judgment underutilized in diffusion research. Given the importance of forecasts before or shortly after launch, methodologies that allow a researcher to incorporate exogenous information and update this information optimally as data become available have an important place in diffusion research.'' We indeed find that combining information across products and countries is superior to combining information across countries or across products alone.[1]

The paper is organized as follows. In §2 we present the methodology for examining the role of various covariates on cross-country diffusion process, §3 describes the expected relationships between covariates and the BDM parameters, §4 describes the data and sources, §5 explains the results and finally, §6 concludes with a discussion of limitations and suggestions for future work.

2. Methodology

2.1. Model

The discrete time version of the Bass diffusion model is as follows:

$$S_{pr,c}(t) - S_{pr,c}(t-1) = \Big(p_{pr,c} + (q_{pr,c}/\alpha_{pr,c})^* S_{pr,c}(t-1)\Big) \times [\alpha_{pr,c} - S_{pr,c}(t-1)] \quad (1)$$

where pr indexes the product and c indexes the country, $S_{pr,c}(t)$ is the per-capita cumulative sales of product pr in country c at time t. We use per-capita sales in the model in order to correct for the influence of scale in countries with widely varying populations and to account for population growth over the time period of analysis. The parameter $\alpha_{pr,c}$ indicates the market penetration potential or ''ceiling'' for the product (Van den Bulte 2000). Since we work with per-capita sales in the model, the total market potential in a country is given by $m_{pr,c}(t) = \alpha_{pr,c}N_c(t)$, where $N_c(t)$ is the population of the country c at time t.

The conditional probability of adoption, $(p_{pr,c} + (q_{pr,c}/\alpha_{pr,c})S_{pr,c}(t-1))$, in the BDM is influenced both directly (captured through parameter $p_{pr,c}$) and through endogenous feedback (captured through parameter $q_{pr,c}$). The parameter $p_{pr,c}$ captures the influence on the adoption decisions of potential adopters that is independent of the existing number of adopters within the country. In contrast, the parameter $q_{pr,c}$ captures the influence of existing number of adopters within the country on potential adopters yet to purchase the new product. The parameters $p_{pr,c}$ and $q_{pr,c}$ are therefore referred to as the *coefficients of external* and *internal influence* respectively (Mahajan et al. 1990)[2]. They thus characterize the communication process through which consumers become aware of and are persuaded to buy a new product, and determine the speed of diffusion of the new product in a country (Van den Bulte 2000). It can be shown that the time, t^*, to peak sales (which is the inflection point of the cumulative penetration curve in the BDM), is equal to $(p_{pr,c} + q_{pr,c})^{-1}\ln(q_{pr,c}/p_{pr,c})$.

For estimation, we use the nonlinear BDM estimation approach proposed by Srinivasan and Mason (1986). In their evaluation of various estimation procedures, Mahajan, Mason, and Srinivasan (1986) find that Srinivasan and Mason's model does best relative to other alternative formulations of the diffusion model on both the reliability and predictive power of the estimates. We incorporate two changes to this model. First, we model the error term on the demand in a multiplicative fashion, as is common in demand modeling and as is done in Van den Bulte and Lilien (1997), to reduce the effects of heteroscedasticity and to prevent the possibility of support for negative demand. Second, to allow for the possibility of serial correlation in errors between successive periods, we also model autocorrelated errors.

More formally, solving for Equation (1), the per-capita sales in period t for product pr in country c, and incorporating a multiplicative error, $S_{pr,c}(t) - S_{pr,c}(t-1)$, is given by the following equation:

$$\begin{aligned} S_{pr,c}(t) &- S_{pr,c}(t-1) \\ &= \alpha_{pr,c}[F_{pr,c}(t) - F_{pr,c}(t-1)]e^{\epsilon_{pr,c}(t)}, \\ &\quad pr \in [1, \ldots, PR], \quad c \in [1, \ldots, C], \\ &\quad t \in [0, \ldots, T], \end{aligned} \quad (2)$$

[1]Neelamegham and Chintagunta (1999) recently used a Hierarchical Bayes model to forecast viewership for movies across countries. They use a linear functional form that is appropriate for forecasting movie viewership. Our focus here is on the estimation of the nonlinear Bass diffusion model since it is more appropriate for durable goods.

[2]In the diffusion literature, the parameters $p_{pr,c}$ and $q_{pr,c}$ are frequently referred to as the ''coefficient of innovation'' and ''coefficient of imitation'' respectively (Bass 1969, Gatignon et al. 1989, Horsky and Simon 1983, Dekimpe et al. 1998). Mahajan et al. (1990) discuss why the innovator-imitator label is inappropriate, because the ''innovators'' are not necessarily the early adopters in the BDM.

where $\epsilon_{pr,c}(t)$ is an autocorrelated error term. Since preliminary estimation showed that errors tend to be homoscedastic across countries for a particular product, and heteroscedastic across products for a particular country, we allow the errors to have a different variance σ^2_{pr}. Also, for reasons of parsimony we allowed the autocorrelation ω_{pr} to vary only across products. $F_{pr,c}(t)$ denotes the CDF for the diffusion process for that product/country pair at time t. This CDF is given by

$$F_{pr,c}(t) = \frac{\{1 - \exp[-(p_{pr,c} + q_{pr,c})t]\}}{\{1 + (q_{pr,c}/p_{pr,c})\exp[-(p_{pr,c} + q_{pr,c})t]\}} \quad (3)$$

with $F_{pr,c}(0) = 0$, $\forall pr, c$. The subscripts on the p, q and α coefficients denote the fact that we allow for heterogeneity in these values across both countries and products. We selected an exponential, nonlinear transform on the three parameters to restrict the actual parameters to be positive, while allowing their transformed values to lie along the full real line to allow estimation of the variance decomposition using the normal distribution. More specifically, using ''*'' to denote the transformed variable:

$$\alpha_{pr,c} = e^{\alpha^*_{pr,c}}, \qquad p_{pr,c} = e^{p^*_{pr,c}}, \quad \text{and} \quad q_{pr,c} = e^{q^*_{pr,c}}. \quad (4)$$

Next, we consider the heterogeneity structure across p^*, q^*, and α^*. We separate each parameter into a component that is common across all countries for a particular product, a component that is common across all products for a particular country, and a component that is unique to that product/country combination. The country and unique components are, in turn, separated into a portion that is explained by a set of regressors and a random component that is allowed to be correlated across parameters. Formally:

$$\begin{bmatrix} \alpha^*_{pr,c} \\ p^*_{pr,c} \\ q^*_{pr,c} \end{bmatrix} = \begin{bmatrix} \alpha^*_{pr} + \alpha^*_c \\ p^*_{pr} + p^*_c \\ q^*_{pr} + q^*_c \end{bmatrix} + \begin{bmatrix} \upsilon_{\alpha,pr,c} \\ \upsilon_{p,pr,c} \\ \upsilon_{q,pr,c} \end{bmatrix}, \quad (5)$$

where the ν vector is the set of unique country/product effects, further decomposed into regressors related to the hypotheses in §3 and a random, idiosyncratic component that is unique to each product/country pair:

$$\begin{bmatrix} \upsilon_{\alpha,pr,c} \\ \upsilon_{p,pr,c} \\ \upsilon_{q,pr,c} \end{bmatrix} = \begin{bmatrix} X'_{\alpha,pr,c}\beta_{\alpha,pr,c} \\ X'_{p,pr,c}\beta_{p,pr,c} \\ X'_{q,pr,c}\beta_{q,pr,c} \end{bmatrix} + \begin{bmatrix} \pi_{\alpha,pr,c} \\ \pi_{p,pr,c} \\ \pi_{q,pr,c} \end{bmatrix},$$

$$\begin{bmatrix} \pi_{\alpha,pr,c} \\ \pi_{p,pr,c} \\ \pi_{q,pr,c} \end{bmatrix} \sim MVN(\mathbf{0}, \boldsymbol{\lambda}). \quad (6)$$

The component that is common across all products for each country is regressed against a set of variables linked to the hypotheses appropriate to that parameter as discussed in §2:

$$\begin{bmatrix} \alpha^*_c \\ p^*_c \\ q^*_c \end{bmatrix} = \begin{bmatrix} X'_{\alpha,c}\beta_{\alpha,c} \\ X'_{p,c}\beta_{p,c} \\ X'_{q,c}\beta_{q,c} \end{bmatrix} + \begin{bmatrix} \pi_{\alpha,c} \\ \pi_{p,c} \\ \pi_{q,c} \end{bmatrix}, \qquad \begin{bmatrix} \pi_{\alpha,c} \\ \pi_{p,c} \\ \pi_{q,c} \end{bmatrix} \sim MVN(\mathbf{0}, \boldsymbol{\gamma}_c). \quad (7)$$

Note that consistent with most research on diffusion, we have assumed that the parameters of the diffusion model are time invariant. Therefore, country-specific covariates are included as timeinvariant. In fact, we used the average value of each covariate for each country over the period of interest. While an argument could be made that time-varying values should be used, the within-country variance for the variables that we use is only 12% of the between-country variance. Hence, we use a simpler model with parameters held constant across time.

We model the product specific component with a random effects model, i.e., without any hierarchical regressors. The random effects distribution is centered about 0, for identification:

$$\begin{bmatrix} \alpha^*_{pr} \\ p^*_{pr} \\ q^*_{pr} \end{bmatrix} = \begin{bmatrix} \pi_{\alpha,pr} \\ \pi_{p,pr} \\ \pi_{q,pr} \end{bmatrix}, \qquad \begin{bmatrix} \pi_{\alpha,pr} \\ \pi_{p,pr} \\ \pi_{q,pr} \end{bmatrix} \sim MVN(\mathbf{0}, \boldsymbol{\gamma}_{pr}). \quad (8)$$

This is a flexible yet parsimonious specification of the heterogeneity across countries and products. There is no attempt to ''force'' the model to conform to any expectations about the nature of heterogeneity. As an example, if it turns out that there is no heterogeneity, observable or unobservable, that is common across countries for α, then $\gamma^2_{\alpha,c}$ would be small relative to $\gamma^2_{\alpha pr}$ and λ^2_α (where γ^2_α, is the first diagonal element of $\boldsymbol{\gamma}$); also, $\beta_{\alpha,c}$ would be insignificant. In this manner, the model allows us to explore the nature of heterogeneity among the parameters in a rich framework across countries and products, both observable and unobservable. This will be discussed in detail in §5.

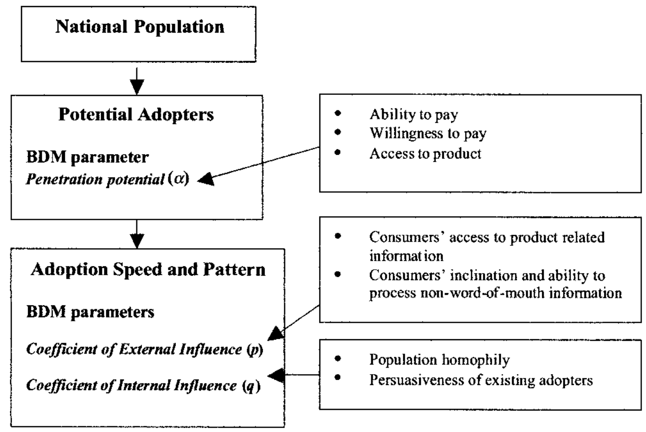
2.2. Estimation

We estimate the above model using the Hierarchical Bayes estimation methodology. Most of the steps above can be estimated using the Gibbs sampler, as the conditional distributions have conjugate priors and well-defined distributions. The exception is the estimation of the parameters in Equations (2) and (3), and the autocorrelation term, which require use of a Metropolis-Hastings step. We selected normal priors that were diffuse, and inverse Gamma/Wishart priors that were tested for robustness. The sequence of estimation steps, the exact prior distributions used, and the code are described in the Appendix.

We now discuss the differences between our estimation methodology and two other closely related papers in the literature. The key differences between this paper and Gatignon et al. (1989) are: (1) They focus only on explaining the coefficient of external and internal influence (p and q) and not the penetration potential (α) as we do in this paper. (2) Their pooling of data is only across countries, and they estimate the model one product at a time. (3) Their estimation methodology is only applicable for linear estimation models and, therefore, they do a two-step estimation procedure of estimating α upfront so that they can linearize the model. Lenk and Rao (1990) use a Hierarchical Bayes approach as we do, but they pool data only across products. Also, their analysis is without any hierarchical regressors and has a simpler error structure. In contrast, we pool data across both countries and products and separate the variance into product, country, and product-country components with hierarchical regressors for the country component.

An important element of the empirical testing of the model outlined above is to test its performance against a simpler benchmark. We choose to test it against two simpler formulations; one of which models all countries for a particular product, similar in kind to the work of Gatignon et al. (1989), and the other of which models all products for a particular country, similar in kind to the study of Lenk and Rao (1990). The model outlined above can easily be simplified for such a scenario. For example, to model a single product's performance across multiple countries, one would drop the subscript pr throughout, and Equations (5), (6), and (8) would be unnecessary. Similarly, to model diffusion in a single country across multiple products, one would drop the c subscript, as well as Equations (5) to (7).

Figure 1 Conceptual Framework



Note that we do not use exactly the same estimation methodologies outlined in Gatignon et al. or Lenk and Rao, as it would then be difficult to determine what aspect of the improvement was due to using our formulation rather than the empirical Bayes, the different error assumptions and other points of difference between one or both of those analyses and ours, and what was due to simultaneous estimation across both countries and products. Since our focus is to study the improvements that are due to simultaneous estimation across both products and countries, we feel that our benchmark is the most appropriate (and also more demanding), as it controls for all other factors. We report the performance of these simplified structures against our model in §4.

3. Expected Role of Covariates

We use the simple conceptual framework shown in Figure 1 to guide our choice of covariates that impact the diffusion process through their influences on the BDM parameters. We note that while our choice of covariates is by no means exhaustive, it encompasses a larger set of variables than any existing study in the international diffusion literature.

Penetration Potential (α)

The diffusion literature recognizes that not everyone who learns about a new product will purchase the product (Horsky 1990). Economic rationale suggests that consumers who adopt a new product are those who have: (1) the ability to pay, (2) the willingness to pay, and (3) access to the product. Hence, countries in which consumers have greater ability and willingness to pay, and have greater access to the product, are likely to have higher penetration potential.

Ability to Pay. We use *Purchasing Power Parity* (PPP) adjusted average income per capita to measure consumers' relative ability to pay across countries.[3] Furthermore, for a given level of average income, a country with a higher concentration in income has fewer consumers with adequate purchasing power to adopt a new product. One common measure of income concentration used in the economics literature is the *Gini Index*, whose value ranges from 0 to 100, with higher values indicating higher concentrations (World Bank 1999). Hence we expect the *Gini Index* to have a negative relationship with penetration potential. In addition to income differences, demographic composition can also moderate consumers' relative ability to pay. For example, a higher *proportion of dependents* (children and elderly) in population can reduce the disposable income of potential adopters in a country. The penetration potential for a product is thus expected to be lower in countries with higher ratios of dependents to working age populations. We note, however, that this would not be necessarily true if we were modeling diffusion of products targeted to children or elders. The willingness to pay effect may dominate the ability to pay effect in that case.

Willingness to Pay. A consumer's willingness to adopt a new product depends on the incremental benefit offered by the product relative to the product that currently serves that need (Horsky 1990). For example, if customers do not have access to a terrestrial phone line (as in many developing countries), they may be willing to more readily adopt a cell phone if it is available. Similarly, a consumer who already owns a complementary product that is needed to use the new product is more willing to pay for it. We thus expect a positive relationship between the *percentage of customers waitlisted for terrestrial lines* (relative to the installed base of terrestrial lines) and cell phone penetration potential, and between the penetration potential of VCRs and camcorders and the TV penetration level in a country. Also, since fax machines need installed telephone lines, we expect that the penetration potential of fax machines will be positively related to the per capita installed base of telephones in a country.

Access to Product. Efficient production and distribution channels enhance consumer access to a new product (Kravis 1970, Lieberman 1993). Macroeconomics studies show that an ''open economy'' fosters greater competition which increases production and distribution efficiency (Ford et al. 1998, Lieberman 1993). Studies in urban economics also show that urban areas are likely to enjoy greater production and distribution efficiency from better infrastructure and economies of scale (Calem and Carlino 1991). These findings suggest that the penetration potential will be higher in countries with more open economies and higher levels of urbanization. Since the extent of international trade is often used to measure the open-

[3]From this point onwards, all GNP per capita dollar measures of countries refer to the corresponding PPP adjusted measures in 1996 constant dollars. The PPP measures account for the differences in prices across countries and thus capture the true differences in purchasing potential of incomes across countries (World Bank 1993). While the routine use of *Currency Exchange Rate* (CER) adjusted average income per capita in existing cross-national diffusion studies (for e.g., Putsis et al. 1997, Dekimpe et al. 1998, 2000b) is reasonable for studies focusing on fairly similar group of countries, it may be inappropriate when analyzing a diverse group of countries (UN 1990). For example, the 1996 CER adjusted average per capita incomes in U.S. dollars for Japan and India were $40,940 and $380 respectively. The corresponding PPP adjusted incomes were $23,420 and $1,580 (World Bank 1999). Such divergence of CER and PPP incomes can distort the true purchasing power differentials across countries.

ness of an economy in the macroeconomics literature (e.g., Leamer 1987), we operationalize openness by computing the percentage of a country's GDP that is accounted by its imports and exports. We measure urbanization in terms of the percentage of population living in urban areas (World Bank 1999).

Coefficient of External Influence (p)

The coefficient p in the BDM captures the influence on potential adopters' decisions that is independent of the existing number of adopters within the country, i.e., the influence that is *not* obtained through interpersonal (word-of-mouth) communication with existing adopters within a country (Horsky and Simon 1983). The strength of such influence is likely to increase with: (1) consumers' access to product-related information (that can be obtained without interpersonal communication with the existing adopters within a country), and (2) consumers' inclination and ability to process information from non-word-of-mouth communication channels.

Consumers' Access to the Product-Related Information. Consumers may interact with people from other countries or use mass media (TV, newspapers) to obtain access to product related information. We measure external contact in terms of number of minutes of incoming and outgoing international phone calls and the access to mass media in terms of penetration levels of TV and newspapers.[4] Also, the longer a product has been introduced in other countries, consumers are likely to have more information about the product (Dekimpe et al. 2000b). The coefficient p is thus expected to increase with the years of lag in new product introduction across countries.

Consumers' Inclination and Ability to Process Non-Word-of-Mouth Information. Since educated consumers are more likely to seek independent confirmation of the attractiveness of a new innovation (Hirschman 1980), they would be more inclined to use non-word-of-mouth sources to make independent judgments about new products. We therefore expect a negative relationship between the coefficient p and illiteracy level across countries.

Coefficient of Internal Influence (q)

The coefficient of internal influence measures the influence of existing number of adopters within a country on purchase decisions of other people yet to adopt the new product in that country. While the strength of such internal influence will obviously depend on the existing number of adopters, the BDM structure explicitly accounts for that. So, the coefficient q in the BDM essentially captures the effectiveness of such internal influence within a country.[5] The coefficient is thus likely to increase with: (1) population homogeneity, and (2) the persuasiveness of consumers who have adopted the product.

Population Homogeneity. Personal interaction and communication are facilitated within homogeneous rather than heterogeneous populations (Takada and Jain 1991). We measure the degree of homogeneity of populations across countries along socioeconomic dimensions. We use the *Gini Index* as a measure of income heterogeneity and the number of distinct ethnic groups as a measure of ethnic heterogeneity (Dekimpe et al. 1998, 2000b), and we expect these measures to have negative impact on the coefficient q. Also, as women enter the labor force in greater numbers, they have greater opportunities to interact with other men and women with a consequent facilitation of greater social communication. This can reduce gender stratification in society and have a positive impact on the coefficient q. Alternatively, one may argue that women entering the labor force can communicate better and become better opinion leaders—which make them more persuasive with their recommendations (an issue we discuss in the next section) and thus also produce a positive impact on the coefficient q. While our empirical analysis cannot separate the role of these two effects, we expect women in the labor force to have a positive impact on the coefficient q in either case.

[4]We also considered other mass media, such as radio. However, since TV and radio penetrations are very highly correlated, we used only TV penetration in the analysis.

[5]Mathematically, the coefficient of internal influence in the BDM captures the marginal impact of existing penetration level on adoption probability of people who have not yet adopted the new product.

Persuasiveness of Existing Adopters. The coefficient q is expected to increase with greater persuasiveness of word-of-mouth recommendations from the existing adopters. The persuasiveness of recommendations in turn will increase with the satisfaction and familiarity of existing adopters with the new product (Takada and Jain 1991). We operationalize the relative level of satisfaction and familiarity of existing adopters in a country for a new product in terms of the number of years that the new product introduction in that country lags behind the introduction in the lead country.[6] A product that has been in the market for several years is more likely to have many of its initial ''bugs'' fixed and would have moved along the experience curve for many manufacturers, leading to a more appealing price-value proposition. At comparable stages of the diffusion process, adopters in lag countries are thus likely to be more satisfied with their product than those in lead countries (Ganesh and Kumar 1996). Furthermore, they are likely to be more familiar with the attributes and benefits of a product, the longer the product has been introduced in a market (Rogers 1995).

In §2 (where we report the estimation results) we also summarize the expected effects of the various country and product covariates on the three parameters of the BDM and note whether these effects have been empirically tested in existing international diffusion studies.

4. Data

Our data set includes 31 countries with sales data for six product categories, introduced at different times during the period from 1975 to 1997—VCR players (introduced in 1976), CD players (1984), microwaves (1975), camcorders (1984), fax machines (1979), and cellular phones (1981). Although adoption (first purchase) data is ideal for estimating the BDM, such data is very difficult to obtain across a wide range of countries, especially for developing countries that we wish to analyze. Accordingly, like all the existing international diffusion studies, we also use sales data. However, to reduce the impact of repeat purchases on our estimates, we use sales data only from within the first nine years of product introduction in a country in our analysis. The countries that we use in our study are listed in Table 1. We assembled the data from a number of sources including international organizations such as the *International Telecommunications Union* (ITU), the *United Nations* (UN), and the *World Bank.* Product sales data are obtained mostly from the databases of the World Bank, ITU, and publications by *Euromonitor* (*European and International Marketing Data and Statistics,* various years). Country data are assembled from various economic and social databases and reports of the UN and the World Bank, which compile such data and reports on a regular basis in cooperation with respective national government agencies and other international organizations.[7]

5. Results

5.1. Hierarchical Regression Results

We report the results of the hierarchical regressions of the diffusion parameters in Column I of Table 2. The estimated effects of the various explanatory variables on the three BDM parameters are mostly consistent with the expected effects hypothesized in the previous section. With respect to the penetration potential, PPP adjusted per capita income shows a strong positive relationship as expected. The estimated positive effects for trade and urbanization support the argument in the

[6]In a recent study, Van den Bulte and Lilien (1997) have shown that not modeling marketing mix effects may exaggerate the coefficient of internal influence (which they refer to as social contagion). For example, a systematic decline in prices or increase in advertising over time can lead to increased adoption, which may be attributed to social contagion if the marketing mix variables are not modeled. We acknowledge this potential limitation of our study, as well as that of all other cross-country studies in which marketing mix data across a range of countries is unavailable.

[7]Data on introduction years across the 6 products and 31 countries used in this study is available at the journal's web site (it can be accessed from ⟨www.informs.org⟩). Readers interested in knowing more about the scope and sources of economic and social data collected by the UN and the World Bank may refer to their respective annual publications, *United Nations Statistical Yearbook* and *World Development Indicators.*

Table 1 Countries Included in the Analysis

North America	Europe	Asia/ Australia	South America
Canada	Austria	Australia	Argentina (d)
Mexico (d)	Belgium	China (d)	Brazil (d)
United States	Denmark	Hong Kong	Chile (d)
	Finland	India (d)	
	France	Malaysia (d)	
	Germany	Philippines (d)	
	Greece (d)	Singapore	
	Ireland	South Korea	
	Italy	Thailand (d)	
	Netherlands		
	Norway		
	Portugal		
	Spain		
	Sweden		
	Switzerland		
	United Kingdom		

Notes: Following the classification by the World Bank, countries marked with (d) are treated as developing countries in our analysis. The classification is based on primarily economic but also social development indices (World Bank 1996).

international and regional economics literature that market deregulation and urban agglomeration lead to greater market efficiency with larger and more varied supply of products and services to consumers (Galal and Shirley 1994). While the relationships between penetration and the presence of complementary products were not found to be significant, many of those relationships are in the right direction and need to be paid further attention to in subsequent studies. We found that modeling the correlations between α, p, and q using the multivariate error structure laid out in Equations (6)–(8) improved the efficiency of the estimates because many of these correlations were high. In general, we find that the error terms of p and q are negatively correlated, while the error terms of $p(q)$ and α are negatively (positively) correlated.

Our findings indicate that for every 1% change in PPP adjusted per capita income, the market penetration potential for a country is likely to change by about 0.3%. Similarly, we find that a 1% change in international trade or urbanization level can potentially change the penetration potential by about 0.5% and 0.2% respectively.[8] The finding is of potential importance in assessing the attractiveness of emerging markets such as China, where such macroenvironmental characteristics are undergoing rapid change. As noted in Table 2, our study is the first to present such empirical insights on penetration potential in the marketing literature.

With respect to the estimated effects of the various variables on the coefficients of external and internal influence (which determine the speed of diffusion), we find a strong negative result for illiteracy level as expected. Our results with respect to the estimated effects of mass media are also in line with our expectations and earlier findings (Tellefsen and Takada 1999). Similar to the findings by Dekimpe et al. (2000b), we find evidence that an increased ethnic diversity in a country is likely to inhibit the social communication process by which consumers learn about a new innovation. Also, consistent with some of the earlier studies, we find a strong positive effect of introductory lag on the coefficient of internal influence (Takada and Jain 1991, Kumar et al. 1998). However, a surprising result is the effect of introductory lag on the coefficient of external influence. Our hypothesis was that as the number of years of lag increased, there would be an increase in the amount of information about the product externally which in turn would lead to an increase in the coefficient of external influence. However, introductory lag shows a negative effect.

With hindsight, we recognize that, unlike the other explanatory variables such as mass media communication and illiteracy level over which managers have no control, introductory lag is a variable that managers can and do control (Melin 1992). A manager will tend to introduce products first into countries where he expects the products to take off faster. We also note that the coefficient of external influence in the BDM measures the probability of adoption at the point of introduction ($t = 0$). Since a small coefficient of external influence slows the take-off of a product, the introductory lag might really be a proxy for firm

[8]Given the exponential transformation in Equation (3), it is easy to see that a 1% increase in a variable whose hierarchical regression coefficient is β will increase α, p, and q by $\exp(0.01\beta)$.

Table 2 Hierarchical Regression Results

Variables	Whether Tested in Existing International Diffusion Studies[a]	Hypothesis About Expected Effect	I (9 Periods, 6 Products) Estimate (*p stat*)[b]	II (9 Periods, 4 Products) Estimate (*p stat.*)
Penetration Level				
Intercept			−1.7850, (0.0)***	−1.5870, (0.0)***
PPP adjusted per capita Income	No	+	0.3125, (0.031)**	0.2931, (0.035)**
Dependents-working people ratio	No	−	−0.1279, (0.189)	−0.0825, (0.26)
Gini index	No	−	−0.0118, (0.457)	−0.1411, (0.153)
Urbanization	No	+	0.1554, (0.100)*	0.1998, (0.042)**
International trade	No	+	0.4882, (0.0)***	0.3869, (0.0)***
TV penetration on VCRs	No	+	0.1196, (0.175)	−0.0103, (0.471)
TV penetration on camcorders	No	+	0.1168, (0.22)	0.1871, (0.089)*
Telephone wait list on cellular phones	No	+	0.1784, (0.142)	—
Telephone penetration on fax	No	+	−0.0718, (0.35)	—
External Influence				
Intercept			−10.2700, (0.0)***	−9.2000, (0.0)***
TV penetration	Yes[c]	+	0.1035, (0.323)	0.1938, (0.112)
Newspapers	Yes[c]	+	0.2523, (0.033)**	0.0853, (0.244)
Illiteracy	No	−	−0.5812, (0.004)***	−0.4429, (0.007)***
External contact	Yes[d]	+	−0.0465, (0.371)	0.0439, (0.361)
Introductory lag	No	+	−1.0120, (0.0)***	−1.0620, (0.0)***
Internal Influence				
Intercept			−0.6607, (0.0)***	−0.7023, (0.0)***
Gini index	No	−	0.0273, (0.202)	0.0634, (0.053)*
Number of ethnicities	Yes[e]	−	−0.0305, (0.098)*	−0.0204, (0.216)
Women in labor force (%)	Yes[d]	+	0.0285, (0.142)	0.0279, (0.168)
Introductory lag (years)	Yes[f]	+	0.0531, (0.032)**	0.0503, (0.068)*

[a]Based on the existing studies that use the BDM. For a good summary of the existing international diffusion studies, refer to Dekimpe et al. (2000a).
[b]We compute Bayesian analog of a *p* statistic. A value of 0.05 means that 95% of the posterior mass lies to one side of 0, and 0.05% to the other side. The asterisks indicate the level of significance: ***1% level; **5% level; and *10% level.
[c]Tellefsen and Takada (1999).
[d]Gatignon et al. (1989).
[e]Dekimpe et al. (1998).
[f]Takada and Jain (1991), Eliashberg and Helsen (1996), Ganesh and Kumar (1996), Ganesh et al. (1997).

information about the relative take off times for different products in different countries. With this perspective it is easy to see why we may find a negative relationship between coefficient of external influence and introductory lag. The introductory lag does not *cause* the reduction in the coefficient of external influence, but the negative relationship indicates that there are unobservable characteristics of a country that reduce the coefficient of external influence, which causes firms to delay entry into these countries.

To put our results in perspective, we compare the ranges of values and means for p and q reported in the meta-analysis of Sultan et al. (1990) with the 95% confidence intervals and means for our model. The range of values reported by Sultan et al. for p is 0.000021–0.03297 with a mean of 0.03, and for q it is

0.2013–1.6726 with a mean of 0.38. In comparison, the 95% confidence intervals and means in our model are for p, 0.000000645–0.003 with a mean of 0.0007, and for q 0.399–0.733 with a mean of 0.528. We find lower means for p and higher means for q in our model compared to Sultan et al. (1990). However we must consider the fact that we have a larger proportion of developing countries in our data set than in any previous study. Since our results show that developing countries have lower coefficients of innovation and higher coefficients of imitation than developed countries, the difference is to be expected and is in the right direction. While Sultan et al. (1990) do not report values for α, Horsky (1990) finds the mean value of α to be 0.805 with a range of 0.57–1.0 across four product categories for the USA. This compares to a mean value of 0.388 (95% confidence interval is 0.03–1.109) in our study.

We tested the robustness of our estimation to data and modeling related issues. We summarize our results briefly here. More details about the robustness checks are available on the journal's website. First we tested the sensitivity of our results to the use of sales data (which are corrupted by repeat purchase data) rather than adoption data, by using data from only seven periods (so as to reduce the impact of repeat purchases). We did not find any significant differences in the hierarchical regression estimates.

The autocorrelation estimates in our analysis are very high and significant. The autocorrelation for the product errors are: VCR players 0.45; CD players 0.81; microwaves 0.955; camcorders 0.681; fax machines 0.85; and cellular phones 0.85. We therefore investigated the importance of modeling serial correlation, since this has not been usually modeled in the literature. Consistent with econometric theory, we found that the efficiency of the estimates improved because we modeled serial correlation, but there was no change in what coefficients are found significant.

Finally, since consumer and business products may have different diffusion patterns, we estimated the model by restricting the analysis to only consumer products (VCR players, camcorder, microwave, and CD players) and dropping cellular phones and fax machines, which are used by both consumers and businesses. The estimates are reported in column II of Table 2. There were hardly any differences in the estimates of penetration level. The effect of newspapers on the coefficient of external influence became insignificant once we dropped the two business and consumer products. This indicates that print media are probably more effective as an information source for business-oriented products than for marketing consumer-oriented products. In contrast the significance levels of TV increased to become very close to a p-value of 0.1, indicating that for consumer products television is relatively more important than newspapers as an advertising medium. With respect to the coefficient of internal influence, the *Gini Index* becomes significant when we consider only consumer products. This is not surprising when one recognizes that greater income disparities in the general population are likely to be less of an impediment to the communication process among potential adopters for products targeted towards businesses than those aimed solely towards individual consumers.

5.2. Variance Decomposition of Heterogeneity

Our methodology permits us to identify the extent to which the characteristics of countries and products affect the heterogeneity in the diffusion process. In particular, we are able to decompose the variance (heterogeneity) into observed and unobserved country effects, unobserved product effects, and observed and unobserved product-country effects. These results are reported in Table 3.

For α^*, the observable country effects are very high at 45.8%. This implies that we can reasonably predict the ultimate level of penetration of a product merely by knowing the values of the macroenvironmental variables used in the hierarchical regression. This is the best imaginable scenario for a new product launch. The second highest level of variance for α^* is in the unobservable product effects, at 39.1%. Hence, ultimate product penetration varies significantly, depending on the product. This implies that knowing the pattern of penetration of the particular product in other countries will assist in making forecasts in a new country. The product-country interaction effects account for little variance, as is also borne out by the

Table 3 Variance Decomposition Across Parameters

Description Equation Component	Country Regressors $\text{var}(x_{i,c}\beta_{i,c})$	Unobserved Country Effects $\gamma^2_{i,c}$	Unobserved Product Effects $\gamma^2_{i,pr}$	Product-Country Regressors $\text{var}(X'_{i,pr,c}\beta_{i,pr})$	Unobserved Idiosyncratic Variance λ^2_i	Total Variance
α^*	0.78	0.11	0.66	0.04	0.10	1.70
	(45.8%)	(6.5%)	(39.1%)	(2.5%)	(6.2%)	
p^*	0.64	0.057	3.54	1.00	2.19	7.43
	(8.6%)	(0.8%)	(47.7%)	(13.4%)	(29.5%)	
q^*	0.0023	0.0088	0.0362	0.0032	0.0224	0.073
	(3.1%)	(12.0%)	(49.6%)	(4.4%)	(30.8%)	

poor p values for these variables in Table 3. It is encouraging that the unexplained idiosyncratic component of variance that is unique to each product/country pair is low at 6.2%.

For p^*, most of the variance is captured by the product effects (47.7%). This implies that little can be learned from previous product launches in a particular country, but understanding the nature of this product's coefficient of innovation in countries where the product was launched earlier can greatly assist in predicting p^* in a new country. The product/country interaction effects are quite strong at 13.4%, demonstrating that the introductory lag variable explains a large percentage of the total heterogeneity in values of p^*. The idiosyncratic component is fairly high, at 29.5%; however, much of the heterogeneity is still predictable.

The values for q^* show the least potential for effective prediction, and at least initially seem to be the most disappointing. The country regressors capture very little, and as was the case for p^*, the majority of the variance is captured by the product effects (49.6%). The idiosyncratic component is high at 30.8%.[9] However, on the positive side, we note that the total variance in q^* is small, approximately 1–5% that of the other two parameters, i.e., this is the parameter that varies least across countries.

Overall, we conclude that α is highly predictable, with a large degree of this heterogeneity coming from observable country effects. Note that p is also highly predictable, with heterogeneity explained almost entirely in terms of the product effects. Finally, q is the least predictable—yet even in this scenario, 49.6% of the variance is captured by product effects, and its variability overall is far lower than the other parameters. In general the findings hold good potential for prediction, although it would be preferable for a practitioner if the country effects were stronger.

These variance decomposition results can aid managers in deciding whether they should weigh past experiences of other products within a country relative to past experiences in other countries where a product was earlier introduced, while forecasting the diffusion of a product in a country where it is being newly introduced. Based on the explained variances, we find that while past experiences of other products in a country (country effects) are relatively more useful to explain penetration level (cumulative sales), past experiences in other countries where a product was earlier introduced (product effects) are more useful to explain the coefficients of external and internal influence (and thus the speed with which the product will attain peak sales).

5.3. Forecast Performance

We now evaluate the relative accuracy of the 1-year and 2-year ahead forecasts from our product-country model (the ''full'' model) against two benchmark

[9]While it is indeed possible that there are better country regressors to explain the variance in q, our variance decomposition for α, p, and q into product, country, and product-country components do not depend on the regressors used, because we allow for unobserved heterogeneity in the hierarchical regressions. We confirmed this by estimating the model without any regressors and obtained similar variance decomposition results for the product, country, and product-country components.

Table 4 Relative Forecast Performance of Full Model

Dependent Variable: Reduction in MSE of Full Model Relative to:	Coefficient	Estimate	Standard Error	t-Stat	*P* Value	% Reduction
Product model on 1 year ahead forecast	Intercept	0.484	0.282	1.714	0.095	23
	Years since Introduction	−0.033	0.027	−1.224	0.229	
Product model on 2 year ahead forecast	Intercept	0.602	0.271	2.216	0.033	17
	Years since Introduction	−0.053	0.026	−2.01	0.051	
Country model on 1 year ahead forecast	Intercept	0.548	0.240	2.277	0.023	36
	Years since Introduction	−0.058	0.053	−1.085	0.278	
Country model on 2 year ahead forecast	Intercept	0.720	0.169	4.258	0.000	27
	Years since Introduction	−0.095	0.037	−2.511	0.012	

models: (1) a model across the full set of countries, one product at a time (the ''product'' model, similar in spirit to Gatignon et al. 1989), and (2) a model across the full set of products one country at a time (the ''country'' model, similar in kind to that of Lenk and Rao 1990). As a forecasting model, one needs to get good predictions from a model as early as possible in a new product's life cycle (Golder and Tellis 1998, Heeler and Hustad 1980), but this is when we have the least data about the product's diffusion in a country. We therefore evaluate the relative accuracy of the full model as a function of the time, since the product has been introduced in the country.

The forecast estimates were produced as follows. Each model was run using all data available in a particular year. The parameters created in this fashion were used to produce predictions of the expected sales in the following 2 years for each product in each country. To minimize the effects of repeat purchases, we did not make predictions or use data past the ninth year after product introduction in any country. This was repeated for all years from 1987 to 1993. We then computed the mean squared errors (''MSE'') between actual and predicted sales for each model.

To measure the improvement in MSE, we ran regressions with the difference in MSE between the product (country) model and the full model as the dependent variable and time since introduction as a dependent variable. We report these regression results in Table 4. As expected, all of the intercepts are positive and significant indicating the full model outperforms both the product and the country models on one-period and two-period ahead forecasts at the period of introduction. To assess the relative improvement of the full model over the benchmarks, we also report the percentage reduction in the MSE by using the full model. We find that the percentage improvement in the forecasts ranges from 17% to 36% by using the full model. Also as expected, all of the coefficients on the time since introduction are negative, indicating that in general the relative accuracy of the full model is greatest in the early stages after product introduction. These coefficients are, however, only significant for the two-period ahead forecasts.

Overall, we conclude from this analysis that the full model improves forecasting accuracy over the product and country models and its value is greatest during the early stage of a product introduction, when the forecast's value is greatest.

6. Conclusion

This study investigated the impact of a wide range of macroenvironmental variables on the parameters of the BDM. Since our empirical analysis covers a diverse set of developed and developing countries from several continents, the findings of our study provide a stronger basis to draw empirical generalizations about international product diffusion process than previously possible. The findings themselves hold substantive implications, especially as rapid globalization requires firms to venture into new international markets as never before.

6.1. Implications

As firms from developed countries seek to expand into markets of major developing countries, an issue of particular interest to them is a good understanding of how the speed and penetration potential of product diffusion differ across countries and what accounts for such differences. The scope of our dataset also enables us to contrast the diffusion process between developed and developing countries. Our study sheds new insights that underscore both the opportunities and challenges for firms diversifying into emerging international markets.

The average penetration potential across developed and developing countries are as follows—α: 0.515 (developed) and 0.171 (developing). Major developing countries like China and India currently have significantly lower levels of per capita income, trade and urbanization than the industrialized countries. For example, USA currently has PPP adjusted per capita income, trade and urbanization levels that are about 9, 3, and 2.5 times more, respectively, than those of China (World Bank 1999). Hence it is not surprising that the average penetration potential for developing countries is about one-third (0.171 versus 0.515) of that for developed countries. However, given the high populations in many developing countries, even a penetration potential of 0.171 signifies huge market opportunities in major emerging markets.

Further, projected outlooks for growth in GNP and international trade are very positive for the major emerging markets (IMF 1999, World Bank 1999). International trade should increase, as trade barriers continue to fall in lieu of memberships in the World Trade Organization (WTO). Also, demographic trends indicate most of the growth in world urban population over the next decade will be in these countries. In fact, more than 90% of the increase in world urban population between 1995 to 2010 is expected to occur in developing countries, which will see an increase of nearly 56% in its urban population over the same period (UN 1998). Given our findings, such economic and demographic trends would indicate a substantial boost to penetration potential of new products in developing countries.

The average parameters for coefficients for external and internal influence were as follows: for p: 0.0010 (developed) and 0.00027 (developing) and for q: 0.509 (developed) and 0.556 (developing). To understand the implications of the difference in the p and q estimates on diffusion speed that can affect a firm's return on investment in a country, we computed the average time to peak sales (cf. Footnote 3) for developed and developing countries. The average time to peak sales was 16.33 years for developed countries and 19.25 years for developing countries. We find that it takes developing countries on an average about 17.9% (19.25 versus 16.33 years) longer to achieve peak sales. This is despite our finding, consistent with previous studies, that diffusion speeds in developing (''lag'') countries are indeed getting a boost from more appealing price-value propositions for new products with delayed introduction. In other words, such boost in diffusion speed enjoyed by developing countries is still more than offset by the adverse impacts of their current macroenvironmental conditions relative to developed countries. The differences between developing and developed countries in current levels of some of those relevant macroenvironmental factors identified by our study underscore the challenge faced by firms. For example, the literacy and TV penetration in USA are about 4 and 3.5 times more respectively than those of China (World Bank 1999).

So, the empirical findings from our study provide generally strong economic argument for the ''rush'' mentality said to be behind the recent surge in investment in major emerging markets (Saywell 2000). At the same time, they also identify key macroenvironmental variables that are likely to be critical in determining the eventual product penetration potential and diffusion speed in these markets. We believe that our study identifies and empirically quantifies the impacts of a much larger set of such relevant variables on the diffusion process than any other single international diffusion study. This is particularly true with regard to our analysis of product penetration potential—a key measure for evaluating attractiveness of international markets. While business managers have relatively little influence on such variables, our findings can still serve as an empirical guide for the variables that they should consider in evaluating diverse international markets and for performing sensitivity analysis with respect to their projected trends.

The study also has implications for managers seeking to combine information about past diffusion patterns across products and countries for better prediction. Our information-efficient estimation technique improves prediction accuracy by sharing information across countries and products in a single coherent framework. We find that our approach is particularly superior in predicting sales and parameter values in the early years of a new product introduction in a new country, when forecast estimates are managerially most useful.

The variance decomposition results give guidelines to managers about what experience they should weight more strongly when forecasting market potential and diffusion speed. We found that while past experiences of other products in a country (country effects) are relatively more useful to explain the ultimate penetration level (cumulative sales), past experiences in other countries where a product was introduced earlier (product effects) are more useful to explain the coefficients of external and internal influence (and thus the speed with which the product can be expected to attain peak sales).

6.2. Limitations and Future Research

In spite of the contributions made in the paper, there are certain limitations, which provide an agenda for future research. While we analyzed the role of a large set of macroenvironmental variables on product diffusion process, we did not investigate the role of marketing mix variables. Although it is a considerably difficult task to collect marketing mix data in a large number of countries for several products, we believe this can help improve the explanatory and predictive power of the model. Furthermore, even though we studied a wide range of countries in this paper, the range of products that we studied was somewhat limited. In order to generalize the results to a larger number of product categories, we need to extend the analysis to include a number of products. Data limitations, of course, again pose a significant challenge to accomplish this task.

Finally, our focus in this paper has been to find country specific explanatory variables that affect the parameters of the BDM and to improve its fit and forecasts by optimally combining information across products and countries. In a recent study, Putsis et al. (1997) impose structure on the nature of the coefficient of imitation, by assuming a mixing process to explain how the level of penetration in one country can affect the penetration process in another country. They find that such a mixing process can improve the fit and forecasts of the diffusion model in their data. Since Putsis et al. focus on neighboring Western European countries across which there is considerable traffic, the mixing process is likely to be very effective there in explaining the process of imitation than in a data set like ours across widely dispersed countries. Nevertheless, as the world increasingly becomes a ''global village,'' such cross-country diffusion processes need to be modeled even across a diverse spectrum of countries as in our dataset. Estimating such a mixing model by efficiently pooling information across products and countries to improve forecasts can be a difficult but rewarding research direction for the future.

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Appendix—Model Estimation

1. Priors

Priors were generally selected so as to have little impact on the posteriors i.e., to be diffuse across the parameter space of interest. The priors were changed to values substantially larger and smaller to test the robustness of these choices, with only slight effects on the results. In all cases the parameters were chosen to have conjugate priors, of the Inverse Gamma (*IG*), Wishart (*W*), Normal (*N*), and Multivariate Normal (*MVN*) families. All priors are denoted using a subscript 0. The priors were chosen as follows:

$$\sigma_{0,pr} \sim IG(1, \sqrt{10}) \quad \forall\ pr, \tag{A1.1}$$

$$\lambda_0^{-1} \sim W(5, 0.1 \cdot I_3) \tag{A1.2}$$

where I_3 is an identity matrix of dimension 3,

$$\gamma_{0,j}^{-1} \sim W(5, 0.1 \cdot I_3), \qquad j \in [pr, c], \tag{A1.3}$$

$$\beta_{0,c,i,d_i} \sim N(0, 100), \qquad i \in [\alpha, p, q], \qquad d_i \in [1, \ldots D_i], \tag{A1.4}$$

where D_i represents the number of hierarchical regressors used for the country-specific component of that parameter,

$$\beta_{0,p,r,c,i,d_i} \sim N(0, 100), \qquad i \in [\alpha, p, q], \qquad d_i \in [1, \ldots D_i], \tag{A1.5}$$

where D_i represents the number of hierarchical regressors used for the country-product interaction component of that parameter,

$$\rho_{pr}^* \sim N(0, 10) \quad \forall\ pr, \tag{A1.6}$$

where ρ_{pr}^* is a transformed variable used to allow the use of a normal distribution, such that $\rho_{pr} = e^{\rho_{pr}^*}/(1 + e^{\rho_{pr}^*})$.

2. MCMC Estimation Steps

In this section, we define the steps of the estimation procedure. A more detailed discussion of the use of the Metropolis-Hastings (M-H) algorithm can be found in Arora et al. (1998). Details of setting up the Hierarchical Bayes Variance Components structure can be found in Ainslie and Rossi (1998).

$$\text{Draw} \quad \left[\begin{bmatrix} \alpha_{pr,c} \\ p_{pr,c} \\ q_{pr,c} \end{bmatrix} \middle| S, \lambda \right] \quad \text{(Metropolis-Hastings).} \tag{A2.1}$$

Let

$$\mathbf{r} = \begin{bmatrix} e^{\alpha_{pr,c}} \\ e^{p_{pr,c}} \\ e^{q_{pr,c}} \end{bmatrix} - \begin{bmatrix} \alpha_{pr,c}^* \\ p_{pr,c}^* \\ q_{pr,c}^* \end{bmatrix},$$

where

$$\begin{bmatrix} \alpha_{pr,c}^* \\ p_{pr,c}^* \\ q_{pr,c}^* \end{bmatrix} = \begin{bmatrix} \alpha_{pr}^* + \alpha_c^* \\ p_{pr}^* + p_c^* \\ q_{pr}^* + q_c^* \end{bmatrix}.$$

The likelihood function for the coefficient is given by:

$$L\left(\begin{bmatrix} \alpha_{pr,c} \\ p_{pr,c} \\ q_{pr,c} \end{bmatrix}\right) \propto \exp[-\mathbf{r}'\lambda^{-1}\mathbf{r}] \prod_{t=1}^{T_{pr,c}} \exp\{-[\ln(S_{pr,c}(t)) - \ln(\bar{S}_{pr,c}(t))]^2/2\sigma_{pr}^2\}$$

where $T_{pr,c}$ represents the number of time periods available for that product; and

$$\bar{S}_{pr,c}(t) = \alpha_{pr,c}\left[\frac{\{1 - \exp[-(p_{pr,c} + q_{pr,c})t]\}}{\{1 + (q_{pr,c}/p_{pr,c})\exp[-(p_{pr,c} + q_{pr,c})t]\}} - \frac{\{1 - \exp[-(p_{pr,c} + q_{pr,c})(t-1)]\}}{\{1 + (q_{pr,c}/p_{pr,c})\exp[-(p_{pr,c} + q_{pr,c})(t-1)]\}}\right].$$

We use the random walk M-H algorithm, using a suitable Normal draw $\boldsymbol{y}$ with variance chosen (during a run-in period) such that the acceptance rate is approximately 30% as a candidate distribution. This draw is added to the current value of the vector of parameters, i.e., using + to denote the candidate draw and y to denote the value of the draw. Then,

$$\begin{bmatrix} \alpha_{pr,c}^+ \\ p_{pr,c}^+ \\ q_{pr,c}^+ \end{bmatrix} = \begin{bmatrix} \alpha_{pr,c} \\ p_{pr,c} \\ q_{pr,c} \end{bmatrix} + \mathbf{y},$$

and we accept the new draw with probability ψ given by:

$$\psi = \min\left[\frac{L\left(\begin{bmatrix} \alpha_{pr,c}^+ \\ p_{pr,c}^+ \\ q_{pr,c}^+ \end{bmatrix}\right)}{L\left(\begin{bmatrix} \alpha_{pr,c} \\ p_{pr,c} \\ q_{pr,c} \end{bmatrix}\right)}, 1\right].$$

Draw

$$[\sigma_{pr} | \alpha, p, q, S, \bar{S}, \rho_{pr}] \quad \text{(Gibbs)},$$

$$\sigma_{pr} \sim IG[1 + n_{pr}^*, \sqrt{(10 + n_{pr}^* s_{pr}^2)/(1 + n_{pr}^*)}],$$

$$pr \in [1, PR], \tag{A2.2}$$

where n_{pr}^* here is the number of observations, i.e., $n_{pr}^* = \Sigma_{c=1}^{C} \Sigma_{t=1}^{T_{pr,c}} 1$, and

$$s_{pr}^2 = \sum_{c=1}^{C} \sum_{t=1}^{T_{pr,c}} \{\ln(S_{pr,c}(t)) - \ln(\bar{S}_{pr,c}(t)) - \rho_{pr} \cdot [\ln(S_{pr,c}(t-1)) - \ln(\bar{S}_{pr,c}(t-1))]\}^2.$$

Draw

$$[\omega_{pr} | \alpha, p, q, S, \bar{S}, \sigma_{pr}] \quad \text{(Metropolis-Hastings).} \tag{A2.3}$$

The likelihood function is given by:

$$L(\omega_{pr}) \propto \exp\biggl(-\frac{1}{2\sigma_{pr}^2}\sum_{c=1}^{C}\sum_{t=1}^{T_{pr,c}}\{\ln(S_{pr,c}(t)) - \ln(\bar{S}_{pr,c}(t)) - e^{\rho^*_{pr}}/(1 + e^{\rho^*_{pr}}) \times [\ln(S_{pr,c}(t-1)) - \ln(\bar{S}_{pr,c}(t-1))]\}^2 - \frac{1}{2\cdot 10}(\rho^*_{pr})^2\biggr).$$

We use a candidate distribution along with an acceptance process as described in step (A2.1):

$$\text{Draw}\quad \left[\lambda \,\middle|\, \begin{bmatrix}\alpha^*_{pr,c}\\ p^*_{pr,c}\\ q^*_{pr,c}\end{bmatrix}, \begin{bmatrix}\alpha^*_{c}\\ p^*_{c}\\ q^*_{c}\end{bmatrix}, \begin{bmatrix}\alpha^*_{pr}\\ p^*_{pr}\\ q^*_{pr}\end{bmatrix}, \begin{bmatrix}X'_{\alpha,pr,c}\beta_{\alpha,pr,c}\\ X'_{p,pr,c}\beta_{p,pr,c}\\ X'_{q,pr,c}\beta_{q,pr,c}\end{bmatrix}\right] \quad \text{(Gibbs)}, \qquad \text{(A2.4)}$$

$\lambda^{-1} \sim W(5 + PR\cdot C,\ 0.1I_3 + \mathbf{s})$, where

$$\mathbf{s} = \sum_{pr=1}^{PR}\sum_{c=1}^{C}\left(\begin{bmatrix}\alpha^*_{pr,c}\\ p^*_{pr,c}\\ q^*_{pr,c}\end{bmatrix} - \begin{bmatrix}\alpha^*_{c}\\ p^*_{c}\\ q^*_{c}\end{bmatrix} - \begin{bmatrix}\alpha^*_{pr}\\ p^*_{pr}\\ q^*_{pr}\end{bmatrix} - \begin{bmatrix}X'_{\alpha,pr,c}\beta_{\alpha,pr,c}\\ X'_{p,pr,c}\beta_{p,pr,c}\\ X'_{q,pr,c}\beta_{q,pr,c}\end{bmatrix}\right) \times \left(\begin{bmatrix}\alpha^*_{pr,c}\\ p^*_{pr,c}\\ q^*_{pr,c}\end{bmatrix} - \begin{bmatrix}\alpha^*_{c}\\ p^*_{c}\\ q^*_{c}\end{bmatrix} - \begin{bmatrix}\alpha^*_{pr}\\ p^*_{pr}\\ q^*_{pr}\end{bmatrix} - \begin{bmatrix}X'_{\alpha,pr,c}\beta_{\alpha,pr,c}\\ X'_{p,pr,c}\beta_{p,pr,c}\\ X'_{q,pr,c}\beta_{q,pr,c}\end{bmatrix}\right)'.$$

Draw

$$[\beta_{i,c,d_i} \mid X_{i,c,d_c},\ i^*_{pr,c},\ i^*_{pr},\ i^*_{c},\ \gamma^2_{i,c}], \qquad i \in [\alpha, p, q], \qquad d_i \in (1, \ldots, D_i) \quad \text{(Gibbs)}. \qquad \text{(A2.5)}$$

For the sake of simplicity, these were treated as a series of univariate draws by subtracting the effect of all other regressors, i.e., form

$$i^*_c = i_c - \beta'_{i,c,-d_i}X_{i,c,-d_i},$$

where the subscript $-d_i$ in $\beta'_{i,c,-d_i}$ and $X_{i,c,-d_i}$ represents the vector of parameter and matrix of regressors less the current element in the regression. Then perform the regression using the priors in (A1.4), $\gamma^2_{i,c}$, the appropriate diagonal element of γ_c for the variance of the error term, and i^*_c as the dependent variable.

Draw

$$[\beta_{i,p,r,c,d_i} \mid X_{i,pr,c,d_{pr,c}}, i^*_{pr,c}, i^*_{pr}, i^*_{c}, \lambda^2_i], \qquad i \in [\alpha, p, q], \qquad d_i \in (1, \ldots, D_i) \quad \text{(Gibbs)} \qquad \text{(A2.6)}$$

as for (A2.5), except using the quantity

$$i^*_{pr,c} = i_{pr,c} - \beta'_{i,pr,c,-d_i}X_{i,pr,c,-d_i}$$

as the dependent variable, the prior established in (A1.5) and using the appropriate diagonal element λ^2_i of λ as the variance of the error term.

$$\text{Draw}\quad \left[\gamma_c \,\middle|\, \begin{bmatrix}\alpha^*_{c}\\ p^*_{c}\\ q^*_{c}\end{bmatrix}, \begin{bmatrix}X'_{\alpha,c}\beta_{\alpha,c}\\ X'_{p,c}\beta_{p,c}\\ X'_{q,c}\beta_{q,c}\end{bmatrix}\right] \quad \text{(Gibbs)}, \qquad \text{(A2.7)}$$

$\gamma_c^{-1} \sim W(5 + C,\ 0.1I_3 + \mathbf{s}_c)$, where

$$\mathbf{s}_c = \sum_{c=1}^{C}\left(\begin{bmatrix}\alpha^*_{c}\\ p^*_{c}\\ q^*_{c}\end{bmatrix} - \begin{bmatrix}X'_{\alpha,c}\beta_{\alpha,c}\\ X'_{p,c}\beta_{p,c}\\ X'_{q,c}\beta_{q,c}\end{bmatrix}\right)\left(\begin{bmatrix}\alpha^*_{c}\\ p^*_{c}\\ q^*_{c}\end{bmatrix} - \begin{bmatrix}X'_{\alpha,c}\beta_{\alpha,c}\\ X'_{p,c}\beta_{p,c}\\ X'_{q,c}\beta_{q,c}\end{bmatrix}\right)'.$$

Draw

$$\left[\gamma_{pr} \,\middle|\, \begin{bmatrix}\alpha^*_{pr}\\ p^*_{pr}\\ q^*_{pr}\end{bmatrix}\right] \quad \text{(Gibbs)}, \qquad \text{(A2.8)}$$

$\gamma_{pr}^{-1} \sim W(5 + PR,\ 0.1I_3 + \mathbf{s}_{pr})$, where

$$\mathbf{s}_{pr} = \sum_{c=1}^{C}\left(\begin{bmatrix}\alpha^*_{pr}\\ p^*_{pr}\\ q^*_{pr}\end{bmatrix}\right)\left(\begin{bmatrix}\alpha^*_{pr}\\ p^*_{pr}\\ q^*_{pr}\end{bmatrix}\right)'.$$

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