INVESTIGATING INTERNATIONAL NEW PRODUCT DIFFUSION SPEED: A SEMIPARAMETRIC APPROACH

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Global marketing managers are interested in understanding the speed of the new product diffusion process and how the speed has changed in our ever more technologically advanced and global marketplace. Understanding the process allows firms to forecast the expected rate of return on their new products and develop effective marketing strategies. The most recent major study on this topic [*Marketing Science* **21** (2002) 97–114] investigated new product diffusions in the United States. We expand upon that study in three important ways. (1) Van den Bulte notes that a similar study is needed in the international context, especially in developing countries. Our study covers four new product diffusions across 31 developed and developing nations from 1980–2004. Our sample accounts for about 80% of the global economic output and 60% of the global population, allowing us to examine more general phenomena. (2) His model contains the implicit assumption that the diffusion speed parameter is constant throughout the diffusion life cycle of a product. Recognizing the likely effects on the speed parameter of recent changes in the marketplace, we model the parameter as a semiparametric function, allowing it the flexibility to change over time. (3) We perform a variable selection to determine that the number of internet users and the consumer price index are strongly associated with the speed of diffusion.

1. Introduction. The diffusion process of a new product describes the growth in the product's penetration level, the proportion of the relevant population who has adopted the new product [Bass (1969)]. For global business managers, a key issue of interest has always been the diffusion process of new products with in and across countries [Chandrasekaran and Tellis (2007); Talukdar, Sudhir and Ainslie (2002)]. The recent unprecedented globalization of the marketplace has only heightened that interest. According to the World Bank (2010), the volume

of trade and direct investments internationally grew by about 126% and 550%, respectively, from 1990–2007. As businesses pursue new international market opportunities in an increasingly "flat world" [Friedman and Wyman (2005)], an especially interesting aspect of international marketing is the speed of new product diffusions [Kohli, Lehmann and Pae (1999); Peres, Muller and Mahajan (2010); Van den Bulte (2000)]. Is there any systematic trend in the speed of the international diffusion of new products over the recent decades? Which factors hasten or slow the process? Insights to these questions hold significant implications for strategic planning of investments for development and introduction of new products [Putsis et al. (1997); Talukdar, Sudhir and Ainslie (2002)].

Not surprisingly, given its strategic importance to businesses, there has been a steady stream of studies in new product diffusion [for a good review of this literature, refer to Chandrasekaran and Tellis (2007) and Peres, Muller and Mahajan (2010)]. This stream of studies primarily focuses on developing and empirically testing predictive models. Typically, these studies use country-specific but time-invariant covariates for diffusion speed parameters to analyze spatial or across-country variation [Talukdar, Sudhir and Ainslie (2002)]. However, when it comes to the specific issue of investigating systematic change over time in the speed of new product diffusion, the literature is quite limited [Peres, Muller and Mahajan (2010)]. Van den Bulte (2000) provides a nice review and critique of this limited stream of literature.

As Van den Bulte (2000) notes, the existing insights on the issue of diffusion speed change are often based on anecdotal evidence from the business press rather than systematic studies. He further points out that the few academic studies in this area typically suffer from shortcomings in their analysis and from the limited scope of their data. For instance, these studies use no formal or use statistically weak methodologies to test for diffusion speed change over time [e.g., Fisher and Pry (1971); Grübler (1990); Clark, Freeman and Hanssens (1984)]. Also, they mainly use data from before the public introduction of the internet and in the United States only. Within this limited set of existing studies, the study by Van den Bulte (2000) represents the most rigorous investigation of new product diffusion speed change to date. Our study extends that study in several important ways—both substantively and methodologically.

First, the scope and generality of the findings from the study by Van den Bulte (2000) is limited by the fact that its data only includes new product diffusions within the United States and only through 1996, before the popular emergence of the internet. As Van den Bulte himself notes, an important research need is a similar study in an international context, especially in developing countries. Recent reviews of the new product diffusion literature also underscore the need for studies that expand the scope to include developing countries [Chandrasekaran and Tellis (2007); Peres, Muller and Mahajan (2010)]. Our study works to fill that need. We cover four new product diffusions in each of 31 developed and developing nations from 1980–2004. Our set of 31 countries accounts for about 80% of the global

economic output and 60% of the global population. The time period of our analysis also encompasses several interesting and relevant world events—for example, the global economic slow-down and stock-market crash from the 1980s, the end of the cold war, and the popular emergence of the internet in the mid-1990s—in the context of investigating change in new product diffusion speed over time.

Second, our study not only provides the needed counterpart in terms of global and post-internet era scope to the study by Van den Bulte (2000), but also uses novel methodological approaches to analyze changes in diffusion speed. Specifically, the model used in Van den Bulte (2000) makes the restrictive assumption that consumers' propensity to adopt a new product remains constant over its diffusion life cycle. In the logistic diffusion model, that is, equivalent to constraining the diffusion speed parameter to be time invariant [Dixon (1980)]. While this assumption makes the empirical estimation of the model parameters simpler, it comes at the cost of imposing the unrealistic premise that consumers would necessarily exhibit the same propensity to adopt a new product in the early phases as in the later phases of its diffusion life cycle. In contrast, we adopt a semiparametric model structure that allows the diffusion speed parameter to vary over the diffusion life cycle of a new product.

It is relevant to point out here that there are previous studies [e.g., Van Everdingen, Aghina and Fok (2005); Xie et al. (1997)] in the new product diffusion literature that have also allowed time-varying diffusion speed parameters. However, such studies are very limited in number [Van Everdingen, Aghina and Fok (2005)]. More importantly, the focus of this limited set of studies is primarily on methods which allow for time-varying diffusion parameters to reduce the out-of-sample prediction error. The studies show that allowing for time-varying parameters does indeed help their models to improve the prediction of future adoptions. However, none of them discuss the parameters' temporal patterns, that is, how the parameters themselves changed over a product's diffusion cycle, other than the difference between their initial (before any data) estimates and the final estimates. Therefore, we cannot specifically compare our findings on parameters' temporal patterns to those from the aforesaid studies. Further, the data used by those studies is quite limited in its scope. For instance, Xie et al. (1997) use data from the pre-internet time period and only within the United States. Similarly, Van Everdingen, Aghina and Fok (2005) use data from the very early phases of the internet era and only within a small and similar group of developed countries in Europe.

Finally, our study also uses a variable selection procedure to develop a parsimonious model from the multitude of potential country-specific covariates available in an international diffusion study. Such data-driven selection of a parsimonious set of country-specific covariates is particularly valuable to business managers when deciding which relevant market indicators to track in a global marketplace.

Taken together, the scope of our data and our methodology enable us to shed insights into several important time-relevant issues that are hitherto missing from the literature on new product diffusions. They include the following: What systematic

patterns do we see in terms of change in international new product diffusion speed since 1980? What are the macro-environmental factors related to global new product diffusion speed patterns? To what extent are such patterns due to changes in the levels of certain country-specific macro-environmental factors versus a change independent of those factors? As the global marketplace has experienced major socio-economic and technological changes over the past three decades with likely consequences on consumers' propensity to adopt new products, insights into the aforesaid questions are especially interesting to both researchers and business managers.

The next section describes our data used in this study. Section 3 and Section 4 provide details of our estimation methodology. Section 5 explains the results and the Appendix concludes.

2. Data.   As noted earlier, the new product diffusion data used in our study consists of four product categories across 31 countries. The product categories are CD players, camcorders, home computers and cellular phones. Data collection for international new product diffusion studies has always been a challenging task [Chandrasekaran and Tellis (2007)]; our own experience in the context of this study proves no exception. The key data for analyzing international new product diffusion is the annual product penetration level—that is, the proportion of the relevant population which has adopted a new product. Ideally, researchers would like to collect the annual product penetration data directly. However, often such data is not directly available, especially for developing countries [Talukdar, Sudhir and Ainslie (2002)]. In such cases, researchers use the more readily available annual product sales data to indirectly compute the corresponding annual product penetration levels as the ratio of the product sales to population levels. However, when using indirectly computed product penetration levels from sales data, it is important to mitigate any potential contamination due to the inclusion of replacement purchases as opposed to only adoption or first purchases in product sales data [Van den Bulte (2000)].

Accordingly, like the existing international diffusion studies [Putsis et al. (1997); Talukdar, Sudhir and Ainslie (2002)], we use direct annual penetration level data whenever it is available, and use indirect or computed penetration level data otherwise. In our set of four product categories, we were able to get direct penetration data for cellular phones and home computers, but had to use sales data to estimate the penetration for camcorders and CD players. At the same time, as has been the practice in the existing diffusion studies [Talukdar, Sudhir and Ainslie (2002)], we use sales data only from within the first seven years of respective product introductions in a country for camcorders and CD players to reduce the contamination of replacement purchases on our estimates. As such, while we have an average of 17 years of data per country for cellular phones and homes computers, we only have 7 years data per country for camcorders and CD players.

TABLE 1
Countries in our sample

Country	% Pop.	% GNI	Country	% Pop.	% GNI
Argentina	0.6	0.96	Italy	0.91	3.06
Australia	0.31	1.19	Malaysia	0.39	0.47
Austria	0.13	0.49	Mexico	1.6	1.96
Belgium	0.16	0.62	Netherlands	0.25	1.01
Brazil	2.88	2.75	Norway	0.07	0.34
Canada	0.5	1.9	Philippines	1.29	0.83
Chile	0.25	0.32	Portugal	0.16	0.39
China	20.19	15.87	Singapore	0.07	0.22
Denmark	0.08	0.33	South Korea	0.75	1.91
Finland	0.08	0.3	Spain	0.67	2.05
France	0.94	3.5	Sweden	0.14	0.53
Germany	1.28	4.44	Switzerland	0.12	0.52
Greece	0.17	0.46	Thailand	0.99	0.98
Hong Kong	0.11	0.43	United Kingdom	0.93	3.65
India	16.94	6.73	United States	4.59	22.3
Ireland	0.06	0.25	TOTAL	57.62	80.76

Source: World Bank (2010)

The overall time period covered by our diffusion data for the four product categories across the selected 31 countries spans 25 years from 1980 to 2004. For the individual product categories, the time periods covered are as follows: CD players (1985–1993), camcorders (1987–1996), home computers (1980–2004), and cellular phones (1980–2002).

Table 1 below lists the 31 countries that we use in our study. As the list shows, it consists of most of the major developed and developing countries and accounts for about 80% of the world economic output and 60% of the world population. Thus, our study has 124 (4 × 31) product-country pairs across a broad representation of developing and developed markets. In the context of international diffusion studies, the scale and scope of our data provide a substantial empirical basis for investigation. For instance, Chandrasekaran and Tellis (2007) note that a substantial data basis in this context should have a sample size of more than 10 countries or 10 products. It is also important to recall here that the overall time period covered by our diffusion data spans 25 years from 1980 to 2004 that saw several interesting and relevant world events in the context of investigating change in new product diffusion speed over time.

Since our data consists of a wide array of disparate country-product pairs over a 25-year period, our diffusion data is particularly interesting, as it contains large variations across countries, across products and over time. To exemplify such variations, Figure 1 plots diffusion trajectories for two of our products for each of the 31 countries over a common period of 1988–2002. As evident from the figure,
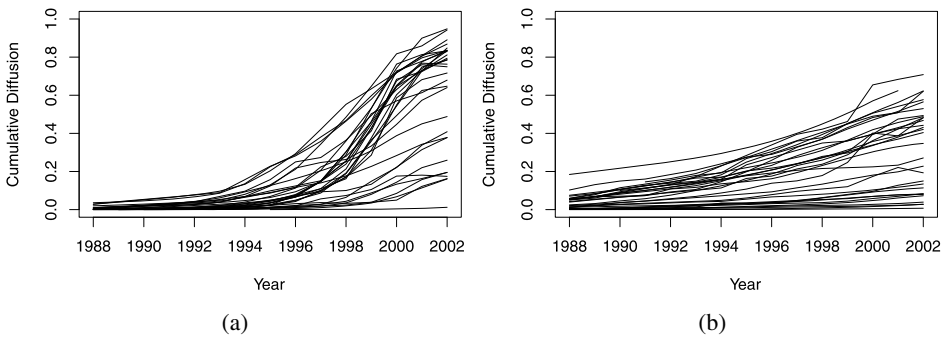
FIG. 1. *Diffusion trajectories for home computers and cellular phones.* (a) *Cellular phones.* (b) *Home computers.*

a comparison across products shows that while the diffusion of cellular phones was slow to take off, it accelerated rapidly after the early 1990s. In contrast, the diffusion of home computers started earlier but its growth has been more gradual. Also, for a given product, the variation in diffusion patterns across countries is readily apparent from the figure, with some countries showing much steeper or faster diffusion than others. For instance, in the case of home computers, our data shows that the United States reached 20% penetration in 1989—five years before the next four countries (Australia, Canada, Norway and Switzerland), although the computer was introduced in all five countries around the same time. In contrast, we find that 10 countries (32% of our sample) did not reach 20% penetration by 2004.

For our study, we were able to get data on 22 relevant country-specific covariates across our sample of 31 countries and for our overall time period of 1984–2004. Such country-specific covariates are essential to analyze what drives variation in diffusion speed across countries, products and over time. Although all our 22 covariates are obviously time-variant, we were able to find annual data for each of our 31 countries over our entire time window (1980–2004) for only 10 of the covariates. These covariates are used in our analysis to specifically capture the temporal variation of diffusion speed within and across countries. For the other 12 covariates, we were unable to get annual data for all the countries and every year in our time window. Such paucity of continuous time-series data on country-specific covariates, especially in the context of developing countries, is quite typical in international diffusion studies [Chandrasekaran and Tellis (2007)]. As in other diffusion studies, we use these covariates as time-invariant country-specific covariates to specifically capture the variation of diffusion speed across countries [Talukdar, Sudhir and Ainslie (2002)]. The list of the covariates is given below (the respective years show the particular year's data used in our analysis for the time-invariant covariates).

Time-varying covariates

- Age dependency ratio: ratio of those in the workforce to those not in the workforce
- Consumer price index
- Electric power consumption (KWH per capita)
- Gross domestic product (GDP) per capita
- Household final consumption: average total expenditure per household
- Internet users (per 1000 people)
- Labor force participation rate, female: proportion of females in the labor force
- Number of telephone mainlines (per 1000 people)
- Unemployment (%)
- Urban population: percent of population living in an urban area

Time-invariant covariates

- Daily newspapers: number of newspapers delivered each day, on average, in 2000
- Ease of doing business index: how conducive is the regulatory environment to business, in 2000
- GINI index: a measure of the inequality of wealth in 2000
- Households with television: percentage of households with a television in 1995
- Individualism index: measure of the degree to which individuals are integrated into groups [Hofstede (2001)]
- International migrant stock: number of migrants in the country in 2000
- International tourism: total tourist entering the country in 1998
- International voice traffic: minutes of international telephone calls in 2000
- Population growth rate in 2000
- Price basket for residential fixed line: average cost of a residential fixed telephone line in 2000
- Pump price for gasoline in 1995
- Uncertainty avoidance index: deals with tolerance for uncertainty and ambiguity [Hofstede (2001)]

Our study data comes from several international organizations such as the International Monetary Fund (IMF), International Telecommunications Union (ITU), the United Nations (UN), the World Bank and the World Tourism Organization (WTO). Specifically, product adoption and sales data for each country are based on annual household and respective industry surveys conducted by various national government agencies. We obtained the data from the country-level databases of the World Bank, ITU and from publications by Euromonitor (European and International Marketing Data and Statistics, various years). As for our various country specific covariates, the socio-economic development indicator databases at the UN, WTO and World Bank served as the sources. Our access to the data is based on specific permission obtained from the various organizations, so unfortunately

we are unable to post the data as a supplement to this article. Interested parties can contact the individual organizations for access details.

3. Methodology.

3.1. *Model.* A review of new product diffusion literature shows that researchers have essentially used two distinct types of models—the logistic diffusion model and the Bass diffusion model [Chandrasekaran and Tellis (2007)]. The key difference in the structure of the two models is that while the logistic diffusion model has a single parameter to capture consumers' propensity to adopt new products, the Bass diffusion model has two such parameters. Since the speed of the diffusion process in either of these two models is expressed in terms of the respective parameters that capture consumers' propensity to adopt new products, the logistic model—with its single parameter—provides a more direct and cleaner relationship between its single parameter for consumers' propensity to adopt a new product and the speed of the diffusion process [Fisher and Pry (1971)]. So, past diffusion studies focused on diffusion speed, like the one by Van den Bulte (2000) noted earlier, used the logistic diffusion model. They have also termed the model's single parameter to be the diffusion growth or speed parameter. Given that the central focus of our study is diffusion speed, we also use the logistic diffusion model as the base model for our analysis.

For the diffusion of a new product in a given country, the basic logistic diffusion model is given by

$$(1) \qquad \frac{y(t)}{Y(t-1)} = \lambda \left[1 - \frac{Y(t-1)}{M(t)\alpha} \right] + \varepsilon(t),$$

where $y(t)$ is the number of adopters in time t, $Y(t-1)$ is the number of cumulative adopters by time $t-1$, $M(t)$ is the population at time t, α is the adoption ceiling parameter (proportion of the population which will eventually adopt the product), λ is the speed parameter (the main focus of our study), and $\varepsilon(t)$ is the error term, $\varepsilon(t) \sim N(0, \sigma^2)$. To analyze the diffusion of 31 electrical household durables in the United States, Van den Bulte (2000) modified the above single product, single country basic logistic diffusion model into a multi-product, single country model. Specifically, his model for product n is

$$(2) \qquad \frac{y_n(t)}{Y_n(t-1)} = \lambda_n \left[1 - \frac{Y_n(t-1)}{M(t)\alpha_n} \right] + \sum_{k \in K_{\mathrm{TV}}} \psi_k X_{kn}(t) + \varepsilon_n(t),$$

$$(3) \qquad \lambda_n = \lambda_0 + \sum_{k \in K_{\mathrm{TIV}}} \beta_k X_{kn} + \varepsilon_n,$$

where K_{TV} is the set of time-varying covariates $X_{kn}(t)$, and K_{TIV} is the set of time-invariant covariates X_{kn}. We augment the model in equations (2) and (3) in three main ways. First and most importantly, we allow the speed parameter (λ)

to vary over the diffusion life cycle of the product. Second, we modify the model to allow for multiple products and multiple countries. Additionally, we perform a variable selection procedure to determine the significant covariates.

3.2. *Multiple products and countries.* To account for the expanded scope of our data in terms of multiple countries and multiple products, we rewrite the model for country i and product n. Because there are only country-specific covariates, we include a product-specific random effect term, τ_n, to account for variation in speed across products:

$$(4) \qquad \frac{y_{in}(t)}{Y_{in}(t-1)} = \lambda_{in}\left[1 - \frac{Y_{in}(t-1)}{M_i(t)\alpha_{in}}\right] + \sum_{k \in K_{TV}} \psi_k X_{ki}(t) + \varepsilon_{in}(t),$$

$$(5) \qquad \lambda_{in} = \lambda_0 + \sum_{k \in K_{TIV}} \beta_k X_{ki} + \tau_n + \varepsilon_{in}.$$

3.3. *Time effect.* As is apparent from its specification in equation (3), the diffusion model used in the study by Van den Bulte (2000) assumes that the speed parameter for a given product remains constant throughout its diffusion life cycle. In this context, it is pertinent to note that the study by Van den Bulte (2000) focused on investigating change in diffusion speed across products introduced in different time periods. So, for that focus, using a model with a time-invariant speed parameter over a given product's diffusion life cycle is reasonable. The assumption of time-invariant speed parameters in a diffusion model also provides two distinct advantages. For one, it makes it relatively easier to empirically estimate such models [Xie et al. (1997)]. It also enables easier derivations of closed-form expressions for the link between the speed parameter and the amount of time it takes to go from one penetration level to a higher one [Van den Bulte (2000)].

At the same time, as noted in our introductory discussion, the assumption of time-invariant diffusion speed parameters imposes the restrictive premise that consumers' propensity to adopt a new product remains constant over its diffusion life cycle. This premise is conceptually at odds with consumers' adoption process in reality, as consumers' propensity to adopt a new product is likely to vary over its diffusion life cycle [Horsky (1990)]. Such variation in consumers' propensity to adopt a new product will be driven by changes in market environments over time that influence consumers' risk attitude and perceived risk of adopting a specific new product and/or new products in general.

Not surprisingly, even though it makes empirical estimation of diffusion models more difficult, researchers now recognize the need to relax the aforesaid restrictive assumption of time-invariant diffusion speed parameters [Van Everdingen, Aghina and Fok (2005); Xie et al. (1997)]. Accordingly, to make our model consistent with this reality, we allow the diffusion speed parameter λ to be time-varying. We should note here that while using the time-variant diffusion speed parameter

makes it more difficult to derive a closed-form expression for the link between speed parameter and the amount of time it takes to go from one penetration level to a higher one, it is still possible under specific conditions (see Appendix A for details).

To allow the diffusion speed parameter λ to be time-varying, we modify our model specification as follows:

$$(6) \qquad \frac{y_{in}(t)}{Y_{in}(t-1)} = \lambda_{in}(t) \left[1 - \frac{Y_{in}(t-1)}{M_i(t)\alpha_{in}} \right] + \varepsilon_{in}(t),$$

$$(7) \qquad \lambda_{in}(t) = f(t) + B_i(t) + \tau_n + \tau_{in}(t),$$

$$(8) \qquad B_i(t) = \sum_{k \in K} \beta_k X_{ki}(t) + \tau_i(t),$$

$$(9) \qquad \tau_{in}(t) \sim N(0, \theta_H), \qquad \tau_n \sim N(0, \theta_A), \qquad \tau_i(t) \sim N(0, \theta_B).$$

As equation (7) shows, we decompose the speed parameter into three components: (1) a common baseline time effect in the form of a nonparametric function, $f(t)$, which depends only upon time, (2) a country-specific term, $\sum_k \beta_{ki} X_{ki}(t)$, which includes all the covariates, and (3) a product-specific random effect τ_n. The country and product effects on the speed parameter are included through the $B_i(t)$ and τ_n terms; so $f(t)$ describes common time-related effects not specific to any one product or country. Additionally, any omitted covariates whose values are highly correlated to the time would also be incorporated in this term (e.g., contemporaneous global macro-environmental trends; expected improvements in quality, price and availability as a product matures). As such, our model specification allows temporal variation in the speed parameter to be driven by changes in both the country-specific covariates as well as by an across-country common time effect. The covariate $X_{ki}(t)$ for the speed parameter λ includes both the time-varying and time-invariant country-specific covariates. Therefore, K is the union of K_{TV} and K_{TIV}. We are able to combine those covariates because we allow our speed parameter to vary over time. In contrast to the model specifications (equations (2) and (3)) in Van den Bulte (2000), this allows us to directly capture the effects of the time-varying country-specific covariates on the speed parameter or consumers' propensity to adopt.

By incorporating a Gaussian residual effect $\tau_{in}(t)$, many of the conditional distributions for the model parameters are now of standard form, greatly increasing our computational efficiency. Conditional on $\lambda_{in}(t)$, equation (7) is independent of $Y_{in}(t)$ and can be written as a standard normal–normal conjugate. This approach of inducing additional random effects has been taken by Holmes and Mallick (2003) and Liechty, Liechty and Müller (2009) in different contexts. We constrained θ_H, the variance of $\tau_{in}(t)$, to be small as suggested in these papers. Using Bayesian adaptive regression splines [DiMatteo, Genovese and Kass (2001)], $f(t)$ is approximated by a cubic spline with k knots in locations $\xi = (\xi_1, \ldots, \xi_k)$, where $a < t_{(1)} < \xi_1 \leq \cdots \leq \xi_k < t_{(n)} < b$. Also, $b_j(t)$, $j \in \{1, \ldots, k+2\}$ is the

j^{th} function in a cubic B-spline basis with natural boundary constraints. Then $f(t) = \sum_{j=1}^{k+2} \omega_j b_j(t)$ for some $\omega_k, k \in \{1, \ldots, k+2\}$. The prior distributions are defined as [Kass and Wasserman (1995)]

$$p(k) = \text{Poi}(2), \tag{10}$$

$$p(\xi) = \text{Unif}(a, b), \tag{11}$$

$$p(\eta|k, \xi) = N(0, 1). \tag{12}$$

The posterior distributions of the ξ and η have dimensions dependent upon k. To estimate the distributions, we use a reversible jump MCMC sampler [Green (1995); Denison, Mallick and Smith (1998); Denison et al. (2002)]. For each iteration of the sampler one of three moves are proposed: birth (add a new knot), death (remove an existing knot), or relocation (move an existing knot to a new location). This method performs well in our case, because the smoothness of the function is chosen automatically and not constrained to be constant across the domain. If there is a sharp change point in our data, this method will discover it. For further information on the implementation of this method, please see Wallstrom, Liebner and Kass (2008).

3.4. *Determining the significant covariates.* In the interest of parsimony, we determine which covariates significantly contribute to the model. The parameter γ_k is a binary variable determining if β_k is significantly different from zero [George and McCulloch (1993); George and McCulloch (1997); Kuo and Mallick (1998)].

The prior distributions for γ, θ_B and β are

$$p(\gamma_i) = \prod_i w_i^{\gamma_i} (1 - w_i)^{(1-\gamma_i)}, \tag{13}$$

$$p(\theta_B) = \text{IG}(\nu/2, \nu\kappa/2), \tag{14}$$

$$p(\beta|\theta_B, \gamma) = N(0, \theta_B D_\gamma R D_\gamma), \tag{15}$$

where D_γ is a diagonal matrix and R is a correlation matrix which we set to be $(X^T X)^{-1}$. The hyperparameters for θ_B were chosen according to the advice in George and McCulloch (1993). They recommend choosing $\kappa = s_{LS}^2$ and then choosing ν so there is substantial probability on the interval $(s_{LS}^2, s_{B_i(t)}^2)$, where $s_{B_i(t)}^2$ is the sample variance of $B_i(t)$ acquired from a pilot run. The ith diagonal element of D_γ^2 is set to

$$(D_\gamma^2)_{ii} = \begin{cases} 0, & \text{when } \gamma_i = 0, \\ \upsilon, & \text{when } \gamma_i = 1. \end{cases} \tag{16}$$

Under those conditions, the marginal distribution of β_i is modeled as

$$p(\beta_i|\theta_B, \gamma) = (1 - \gamma_i)I_0 + \gamma_i N(0, \theta_B \upsilon), \tag{17}$$

where I_0 is a point mass at 0. Following the suggestions in George and McCulloch (1997), we set the value of υ to $\upsilon_\beta/\hat{\theta} = 0.122/0.017 = 7.00$, where υ_β is an estimate consistent with the expected β values (we used the standard deviation of the least-squares estimates) and $\hat{\theta}$ is the LS estimate of θ. In the interest of parsimony, we chose w to be 0.1.

When γ_k equals one, the covariate is included in the model. When it equals zero, the coefficient for that covariate is not significantly different from zero. Because we draw γ_k values from their posterior distribution in each iteration of the algorithm, we can determine the posterior probabilities of significance for each of the covariates by simply finding the proportion of draws which return a one.

It is possible that the set of selected covariates is dependant upon the order in which they are sampled [for further exposition, see, e.g., Heaton and Scott (2010)]. To overcome that potential problem, we randomly determine the order in which the γ_k values are sampled in each iteration and run multiple simultaneous chains to check convergence.

3.5. *Other prior specifications.* The adoption ceiling (α) is bounded both above and below. It is bounded above by one and below by the maximum cumulative adoption for the product-country pair observed in our data ($\max(Y_{in}(t))$). The prior distribution for α is taken to be uniform on that interval.

The precision parameters not involved in the variable selection are given relatively noninformative prior distributions

$$(18) \qquad p(\theta_L) = \text{Ga}(10^{-5}, 10^{-5}),$$

$$(19) \qquad p(\theta_A) = \text{Ga}(10^{-5}, 10^{-5}).$$

The details of the sampling algorithm are available in Appendix B. The algorithm was implemented in R and the code is available as a supplement to this article [Hartman, Mallick and Talukdar (2011)].

4. Results.

4.1. *Variable selection results.* After running the model with the chosen hyperparameters 100 times, we obtained the following results. Figure 2 plots kernel density estimates for the posterior inclusion probabilities for all the possible covariates. We see that the probabilities are relatively consistent across runs. The two covariates with all of their mass above 0.5 are the internet penetration level and the consumer price index (CPI). Electric power consumption only had 19% of its mass above 0.5 and households with television had less than 1% above 0.5; so we conclude that they do not have significant effects. The β estimates were consistent across sampler runs, with regular and unimodal posterior densities. The estimates for the coefficients for CPI and internet penetration level are -0.081 and 0.123 respectively. Because all the covariates are standardized to have a mean of zero and
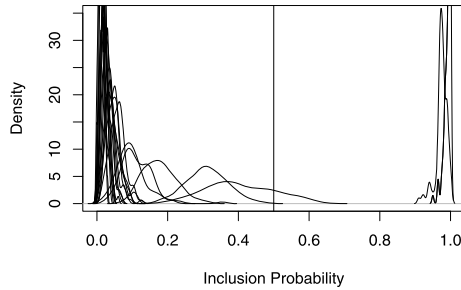
FIG. 2. *Posterior inclusion probabilities for each covariate.*

a standard deviation of one, the absolute size of the estimates are less informative than the sign of the estimates.

The variable selection results are consistent with the expected negative role of the CPI. As the cost of living rises with inflation and CPI, it adversely affects consumers' discretionary income and thus their willingness and ability to pay for new products introduced in the marketplace [Horsky (1990); Talukdar, Sudhir and Ainslie (2002)]. The results also follow the expected positive role of internet access on the speed of a behavior process, that is, fundamentally driven by information flow among the adopting population. In this context, it is relevant to point out that past studies using data from the pre-internet period have included TV and newspaper penetration levels as covariates of diffusion speed parameters to recognize the role of mass media on diffusion process [Putsis et al. (1997); Talukdar, Sudhir and Ainslie (2002)]. Consistent with those past studies, our findings underscore the strong role of the new mass medium represented by the internet, which has fundamentally altered how consumers and firms search for, store and transmit product related information, as well as buy and sell products [Ratchford, Talukdar and Lee (2007)]. The internet also helps speed up the adoption process by acting as a product complement for one of the products (home computers) in our study.

4.2. *Prior sensitivity.* The variable selection results can be highly sensitive to the prior specification. To test the prior sensitivity of the results, we performed the analysis ten times for all possible combinations of the following values for the hyperparameters (300 total runs):

$$\upsilon \in \{1, 5, 7, 10, 15, 20, 25, 50, 100, 500\},$$

$$w \in \{0.1, 0.3, 0.5\}.$$

The inclusion probabilities for all the covariates are plotted in Figure 3, with the iterations then sorted by the average inclusion probability over all the covariates.

Two of the covariates (internet penetration level and the consumer price index) are significantly above the others regardless of the hyperparameter settings. The
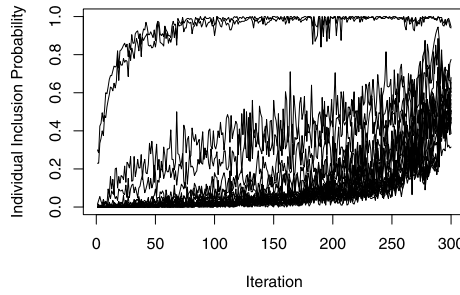
FIG. 3. *Prior sensitivity of variable selection.*

prior specification obviously has a large effect on the inclusion probabilities. Table 2 contains the average inclusion probabilities for various hyperparameter settings. The hyperparameter υ is negatively related to inclusion probability and w is positively related, but the chosen covariates are largely invariant to the settings.

4.3. *Adoption ceiling.* As noted in Van den Bulte (2000), ceiling and speed parameters tend to be negatively correlated and data with a shorter time series tend to have lower estimates of the adoption ceiling parameter. However, this observation is based on diffusion model specifications which impose a time-invariant structure on the speed parameter. An interesting issue is whether the observation still holds for a model, as in our study, which allows the speed parameter to in fact vary over time. In fact, contrary to the observation, we find a slightly positive correlation coefficient ($r = 0.203$) between the adoption ceiling and speed parameter estimates for our four products. We also checked whether our adoption

TABLE 2
Marginal inclusion probabilities

υ	w			
	0.1	**0.3**	**0.5**	**Marginal**
1	0.20	0.38	0.55	0.37
5	0.16	0.28	0.46	0.30
7	0.15	0.25	0.39	0.26
10	0.13	0.20	0.33	0.22
15	0.13	0.18	0.26	0.19
20	0.11	0.16	0.22	0.17
25	0.11	0.15	0.21	0.16
50	0.09	0.13	0.16	0.13
100	0.08	0.11	0.14	0.11
500	0.04	0.07	0.09	0.07
Marginal	0.12	0.19	0.28	0.20

TABLE 3
Adoption ceiling parameter estimates

Product	Mean	95% Credible interval
Cell Phone	0.8001	(0.6069, 0.9840)
Home Computer	0.6802	(0.6010, 0.9468)
Camcorder	0.7998	(0.6100, 0.9899)
CD Player	0.7973	(0.6096, 0.9897)

ceiling parameter estimates are in line with those in past studies, especially for the CD players and camcorders, as those series have only 7 years of data for each country. The mean and 95% credible intervals for the adoption ceiling parameter are in Table 3. We find the estimates to be quite consistent with the findings from other studies [Talukdar, Sudhir and Ainslie (2002)]. In this context, it is pertinent to point out that the study by Van den Bulte (2000), like our study, also does not find any systematic bias in its estimates of adoption ceiling parameters for products like camcorders and CD players with shorter data series.

4.4. *Time component.* Our focal interest in this study is the temporal trajectory of the diffusion speed parameter. In the context of new product diffusion, there are two distinct ways we could measure time: calendar year and year since new product introduction. Also, as noted earlier, our model specification allows temporal variation in the speed parameter to be driven by changes in the country-specific covariates as well as a common time effect captured through the nonparametric function $f(t)$. For the purpose of testing alternative models within our overall model structure, we can use either measure of time or remove $f(t)$ from the model completely. We compared the various alternative models by keeping the prior settings common and then using DIC [Spiegelhalter et al. (2002)]. Table 4 describes the results of the model comparison. $\bar{D}$ is a measure of how well the model fits the data. P_D is the effective number of parameters which is used as a complexity penalty. P_D is different from the nominal number of parameters, especially in hierarchical models. Two models may have the same number of nominal parameters, but if one model is more identifiable and precise, it will have a smaller number of

TABLE 4
DIC results

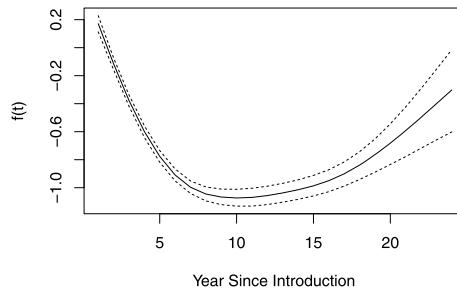| Time measure	$\bar{D}$	P_D	DIC
Year since introduction	−5654.05	1054.10	−4599.95
Calendar year	−5645.56	1057.42	−4588.15
N.A. (Time-invariant)	−5638.83	1057.17	−4581.66

FIG. 4.   *f(t) against year since introduction.*

effective parameters [Congdon (2006)]. DIC is the sum of those two values. In all cases, a smaller number is better.

Based on the DIC values, we find that a time-varying speed parameter with time measured in terms of either the calendar year or the year since product introduction provides a better fit than using a time-invariant speed parameter. Additionally, using year since introduction provides the best fit and fewer effective parameters. Our findings show that modeling the diffusion speed with a time-invariant speed parameter adversely affects the precision and identification of the parameters in the model. Even though the nominal number of parameters is greater when using the number of years since the introduction, the effective number of parameters in fact gets smaller. Our findings thus underscore the value for new product diffusion models in relaxing the typical restrictive assumption of time-invariant diffusion speed parameters, and corroborate similar conclusions from past studies [e.g., Van Everdingen, Aghina and Fok (2005); Xie et al. (1997)].

Figure 4 plots the estimated posterior distribution of $f(t)$ against the number of years since the introduction of the product in each country. The solid line is the pointwise posterior mean, and the dashed lines are the 95% pointwise credible interval bounds. The plot sheds interesting insights into the patterns of the diffusion speed parameter $\lambda(t)$ based on the common time effect induced by the time-correlated product and general macro-environmental trends. The plot clearly shows that there is a systematic temporal trend in the speed parameter—thus, in the underlying consumers' propensity to adopt a new product–over a product's diffusion life cycle. Specifically, the diffusion speed parameter is found to exhibit a U-shaped pattern with respect to the time since a new product's introduction in a country.

Our finding of the U-shaped temporal pattern in the diffusion speed parameter since a new product's introduction in a country indicates that consumers' propensity to adopt a new product goes through a relative drop in its value from the initial phase of the diffusion cycle before climbing back. While our analysis does not provide any direct causal insight as to why we see such a temporal pattern in consumers' propensity to adopt a new product since its introduction in a country,

the pattern appears to be consistent with expectations based on conceptual notions and empirical evidence in the diffusion literature. For instance, the initial phase of a new product's diffusion in a country is primarily driven by the so-called early adopters or consumer innovators [Bass (1969); Chandrasekaran and Tellis (2007)]. The early adopters as a consumer segment represent a relatively small proportion of the eventual adopters for the new product, but by nature they have a higher propensity to adopt and are the first consumer groups to adopt a new product. Our finding of consumers' propensity to adopt starting high and then declining is also consistent with the likely effect of promotion by businesses which accompanies the launch of a new product in a country [Golder and Tellis (1997)]. Such promotion usually has the highest intensity at introduction to generate consumer awareness and interest for the product, but then declines to a lower but steady level as businesses rely more on word-of-mouth from the early adopters. However, the early adopters are followed by the laggards or late adopters [Chandrasekaran and Tellis (2007)] with lower propensity to adopt the new product.

At the same time, as time passes since the introduction, the risk perception among consumers toward adopting a new product declines with better quality, price and availability on the supply side. That in turn will have a positive impact on the value proposition of the new product on the demand side, thereby increasing the propensity to adopt the new product among late adopters [Horsky (1990)]. In our study, these later years specifically include cellular phones and home computers, and reflect the time period from the early 1990s to 2004. Both the products over this time period saw steep decline in price even as their quality and the scope of their use in everyday life improved significantly [Blinder (2000); Chwelos, Berndt and Cockburn (2008); Lawal (2002); Merkle (1998); Prensky (2001)]. Globally, that has not only made consumers more appreciative of the value of these products in their everyday life but also more willing to pay for them [Talukdar, Sudhir and Ainslie (2002)].

As noted earlier, the function $f(t)$ in our model specification of the diffusion speed parameter will reflect not only the effect of product-specific covariates that are highly correlated with time but also the effect of contemporaneous global macro-environmental trends. In that context, it is relevant and interesting to observe here that the early time periods in the diffusion cycle of our products span the early 1980s and early 1990s. This time period saw high levels of economic anxieties and unemployment across the globe driven by two recessions and a stock-market crash (1987) in the United States. On the other hand, the later time periods in the diffusion cycle of our products span the late 1990s and early 2000s. That time period, in contrast, witnessed some singular global macro-environmental trends. For instance, it saw unprecedented trends in economic policy liberalization and digitization of key aspects of market economies all over the world [Gilpin and Gilpin (2001)]. These trends had a profound impact on the global flow of goods, capital and labor—essentially on factors creating the flat world [Friedman and Wyman (2005)]. They also continue to have significant impact on how product
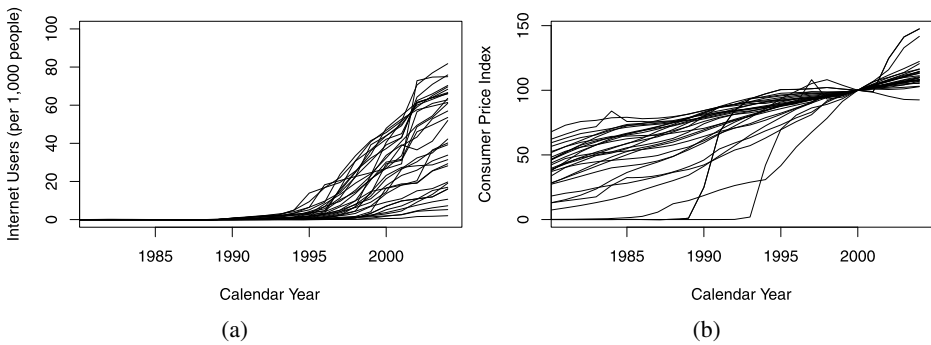
FIG. 5. *Variation in selected covariates across countries and over time.* (a) *Internet users (per* 1000 *people).* (b) *Consumer price index.*

information is disseminated and products are sold by firms as well as how they are searched for and purchased by consumers. Based on economic rationale [Horsky (1990)], all the above global macro-environmental trends are likely to boost consumers' likelihood of adoption of new products in general, and especially of cellular phones and home computers—consistent with our findings discussed earlier about the temporal pattern of $f(t)$ in the later stages of the diffusion cycle in Figure 4.

Further, in our model specification, the temporal variation in the diffusion speed parameter is not just driven by the common time effect captured through the function $f(t)$. It is also driven by changes in the country-specific time-varying covariates. Since the two covariates (internet penetration level and consumer price index) identified through our variable selection analysis are both time-varying, we thus need to include them when looking at the time trend patterns of the diffusion speed parameter. Figure 5 plots the two selected covariates against calendar year for each country. Consumer price index (CPI) is calibrated by setting the year 2000 value to 100. As evident from Figure 5, CPI has increased over our time window. As for internet penetration level, it first grew above zero in 1989, but did not dramatically increase until the introduction of Netscape in 1995 [Friedman and Wyman (2005)].

Now that we have all the individual time-varying components, we can exponentiate the sum of the components to examine how the diffusion speed parameter, $\lambda_{in}(t)$, has changed over calendar time. Figure 6 plots the expected value of $\lambda_{in}(t)$ over the calendar time covered by our analysis across the four products. Since the time period covered for each product is different, it is also instructive to look at similar plots (see Figure 7) separately for each product. Looking at the plots in Figures 6 and 7, it is apparent that there are two separate time periods corresponding to two distinct time-trends in the expected value of the speed parameter. From 1980 to the early 1990s, the countries had significant variations in terms of CPI but very little in terms of internet penetration levels. At the same time, we find the
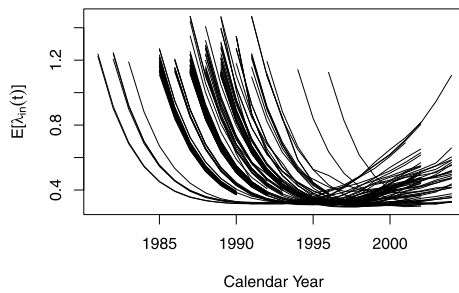
FIG. 6. *Expected trajectory of the diffusion speed parameter.*

expected value of the speed parameter for each product and country pair during this time period to be relatively parallel. That suggests that during that period the expected value is dominated by the $f(t)$ term. Consumers' propensity to adopt new products during this time period declined and was primarily driven by a common time effect across the countries rather than by any country-specific covariate effects.

As for the time period between the mid-1990s to 2004, our analysis covers the later stages of the diffusion cycle for two of the products, viz., cell phones and
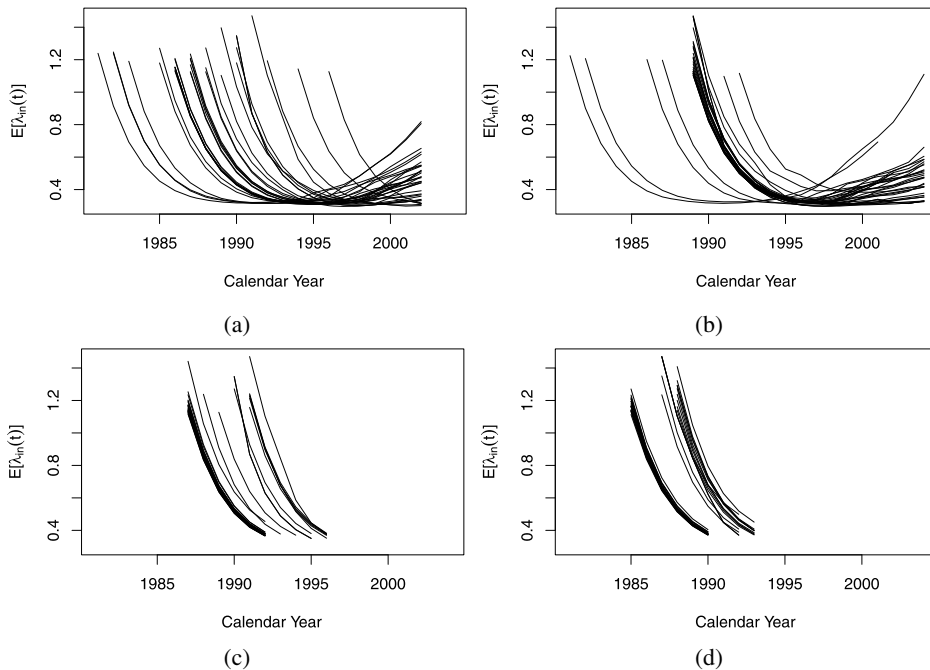

FIG. 7. *Expected trajectory of the diffusion speed parameters for each product.* (a) *Cell phones.* (b) *Home computers.* (c) *Camcorders.* (d) *CD players.*

TABLE 5
Expected value of the diffusion speed parameter for home computers

Country	Expected value	Country	Expected value
Argentina	0.482	Italy	0.474
Australia	0.494	Malaysia	0.473
Austria	0.474	Mexico	0.534
Belgium	0.466	Netherlands	0.491
Brazil	0.559	Norway	0.491
Canada	0.487	Philippines	0.510
Chile	0.509	Portugal	0.493
China	0.478	Singapore	0.493
Denmark	0.485	South Korea	0.504
Finland	0.508	Spain	0.468
France	0.457	Sweden	0.512
Germany	0.467	Switzerland	0.480
Greece	0.546	Thailand	0.464
Hong Kong	0.495	United Kingdom	0.481
India	0.588	United States	0.502
Ireland	0.461		

home computers. Except for a few exceptions that we note below, we find the expected value of the speed parameter for each country for both these products not only reversing direction but also showing distinctive differences in that upward trend. Coupled with our earlier finding in Figure 4, this finding suggests that the positive impacts of common time effect and country-specific internet penetration effects dominated the negative impacts of country-specific CPI effects on consumers' propensity to adopt new products from the mid-1990s to 2004. We should note here that there are a few exceptions to the observed U-shaped temporal pattern in the diffusion speed parameter over the entire time period from the 1980s to the 2000s. Specifically, the expected speed parameters for five home computer (Argentina, Brazil, Greece, India and the Philippines) and four cellular phone (Argentina, Brazil, India and the Philippines) series start high and drop to a low, but do not significantly increase toward the end of our data. Interestingly, both Argentina and Brazil had the highest inflation of the countries in our set. Such high inflation is expected to depress the speed parameter through its negative relationship with CPI. The other three countries also had high inflation (all in the top seven of our set), but they were mainly affected by a late introduction year (they were late in home computers and actually were the last three to introduce cell phones).

For an illustration of the estimated values of the diffusion speed parameter across the countries, we show in Table 5 the expected values of the speed parameter for home computers by country. All of the expected values of the speed parameter are between 0.35 and 0.60, with an average value of 0.49 and a standard deviation of 0.03. For our entire data set, the expected values of the speed

parameter have a mean of 0.55 and a standard deviation of 0.27 across all the 124 product-country pairs. These mean estimates of the time-varying speed parameter are well within the range seen in the past studies [Sultan, Farley and Lehmann (1990); Van den Bulte and Stremersch (2004)]. It is also interesting and pertinent to note here that while there are very few past studies of diffusion in developing countries, those studies found that developing countries often show higher speed at comparable stages of their diffusion cycle [Talukdar, Sudhir and Ainslie (2002); Takada and Jain (1991)]. The accepted rationale is that developing countries generally experience a lagged national introduction of a new product. Such lag in fact has a positive effect on diffusion speed, as it means that some developing countries had not only conducive macroeconomic conditions for adoption but also the advantage of less adoption risk perception (through better product price and/or quality) by their consumers at comparable stages of the diffusion cycle [Chandrasekaran and Tellis (2007); Takada and Jain (1991)]. As Table 5 shows, we also find several developing countries like India and Brazil exhibiting relatively higher values of the diffusion speed parameter for home computers.

5. Conclusion. Understanding the dynamic nature of new product diffusion speed is essential for global marketing managers to make informed decisions. Our paper provides one of the most comprehensive studies of international new product diffusion speed from both a substantive and methodological perspective. First, recent reviews of the new product diffusion literature underscore the need for studies that expand the scope to include developing countries [Chandrasekaran and Tellis (2007); Peres, Muller and Mahajan (2010)]. Our study works to fill that need by using a data set that includes 31 developed and developing countries that account for about 80% of the global economic output and 60% of the global population. The time period (1980–2004) analyzed includes several global events—for example, the popular emergence of the internet—that are relevant in the context of investigating change in international new product diffusion speed over time. Second, our study uses a novel methodology to analyze the changes in diffusion speed. Specifically, we use a semiparametric model to allow the diffusion speed parameter to be time-variant. We also use a variable selection procedure to develop a parsimonious model from the multitude of potential covariates available in an international diffusion study.

Taken together, the scope of our data and our methodology enables us to shed insights into several important issues that are hitherto missing from the extant literature on new product diffusions. By relaxing the assumption of a time-invariant speed parameter over the diffusion cycle of a new product [Van den Bulte (2000)], we show that the speed parameter is generally higher at its introduction, falling to a low in the middle of the diffusion process, and increasing again in the later stages. Also, our global data set allows us to show that this phenomenon occurs not only in developed nations but also in developing ones. Putting our findings in a broader context, we find that the global new product diffusion speed increased

from the mid-1990s to 2004, a time period which saw sustained global economic expansion driven by a high level of globalization and the ushering in of the digital age [Friedman and Wyman (2005)]. Through our variable selection analysis, we find that the internet penetration level and the consumer price index in a country are highly associated with the speed of new product diffusion.

In conclusion, given the scope of our data and our methodology, we have been able to shed several interesting insights into new product diffusion speed. We hope our research serves as an impetus for more work in international new product diffusion. An example of future research directions from a methodological perspective could be to relax the assumption of a time-invariant adoption ceiling parameter that has been used in both past studies and this study. Additionally, the scope of our data could be expanded to include product-specific covariates. Although collecting such information in itself—especially for developing countries—will be quite challenging, the collected data can be easily incorporated into our hierarchical model structure above the τ_n terms. While the function $f(t)$ incorporates product-specific covariates highly correlated with time, more data would allow our model to account for those covariates which are relatively uncorrelated with time.

APPENDIX A: CALCULATION OF THE TIME FROM ONE PENETRATION LEVEL TO ANOTHER

The speed parameter [denoted in this paper by λ, and by β in Van den Bulte (2000)] in the logistic diffusion model conceptually represents consumers' propensity to adopt a new product through a social-contagion based diffusion process. The analytical structure of the standard logistic diffusion model is given by

$$(20) \qquad x(t) = \lambda F(t-1)[M - X(t-1)],$$

where $X(t)$ is the cumulative number of adopters at time t, $x(t)$ is the incremental adoption at time t, M is the number of eventual adopters, and $F(t) = X(t)/M$ is the penetration level at time t. The speed parameter λ affects the slope and displacement of the logistic diffusion curve, and has thus an intrinsic relationship to the speed of the underlying diffusion process. To see this relationship, from equation (20) we get

$$(21) \qquad \frac{X(t) - X(t-1)}{M} = \lambda \frac{X(t-1)}{M}\left[1 - \frac{X(t-1)}{M}\right],$$

$$(22) \qquad F(t) - F(t-1) = \lambda F(t-1)[1 - F(t-1)],$$

$$(23) \qquad \frac{dF(t)}{dt} = \lambda F(t)[1 - F(t)],$$

$$(24) \qquad \int \lambda \, dt = \int \frac{dF(t)}{F(t)[1 - F(t)]}.$$

Assuming the speed parameter λ is time-invariant, it is quite easy to solve the integral in equation (24) to get a closed-form solution for the relationship between λ and the speed of the underlying diffusion process. For instance, the time $(t_2 - t_1)$ that it takes for the diffusion process to go from one penetration level, p_1, to a higher level, p_2, is equal to

$$(25) \qquad t_2 - t_1 = \lambda^{-1} \int_{p_1}^{p_2} \left[\frac{1}{F(t)[1 - F(t)]} \right] dF(t),$$

$$(26) \qquad \Delta t = \lambda^{-1} \ln \left[\frac{(1 - p_1)p_2}{(1 - p_2)p_1} \right].$$

On the other hand, assuming that the speed parameter λ is time-variant, the intrinsic mapping of the parameter λ to the speed of the diffusion process is more difficult to derive as a closed-form solution like equation (26), because the solution comes from equation (27) rather than equation (24):

$$(27) \qquad \int \lambda(t) \, dt = \int \frac{dF(t)}{F(t)[1 - F(t)]}.$$

Obviously, equation (27) can still be solved numerically. However, the availability of a closed-form solution will depend on the specific functional form of $\lambda(t)$. For instance, if $\lambda(t)$ is specified as a linear function of t, meaning $\lambda(t) = \lambda t$, the solution will be

$$(28) \qquad \Delta t = \frac{2}{\lambda(t_1 + t_2)} \ln \left[\frac{(1 - p_1)p_2}{(1 - p_2)p - 1} \right].$$

APPENDIX B: POSTERIOR COMPUTATION

Samples from the posterior distributions of the parameters are drawn using the following algorithm.

1. Draw the precision parameters from the following full conditional distributions:

$$(29) \qquad s_1^2 = \sum_{n=1}^{N} \sum_{i=1}^{I} \sum_{t \in T_{in}} \left\{ \frac{y_{in}(t)}{Y_{in}(t-1)\lambda_{in}(t)[1 - Y_{in}(t-1)/(\alpha_{in}M_i(t))]} \right\}^2,$$

$$(30) \quad p(\theta_L|\cdot) = \mathrm{Ga}\left(10^{-5} + \frac{\sum_{n=1}^{N} \sum_{i=1}^{I} T_{in}}{2}, 10^{-5} + \frac{s_1^2}{2} \right),$$

$$(31) \qquad s_2^2 = \sum_{n=1}^{N} \sum_{i=1}^{I} \sum_{t \in T_{in}} \{ [\lambda_{in}(t)] - f(t) - \tau_n - B_i(t) \}^2,$$

$$(32) \quad p(\theta_A|\cdot) = \mathrm{Ga}\left(10^{-5} + \frac{N}{2}, 10^{-5} + \frac{\sum_{n=1}^{N} \sum_{t \in T_i} \tau_n^2}{2} \right),$$

$$(33) \quad p(\theta_B|\cdot) = \mathrm{Ga}\left(10^{-5} + \frac{I}{2}, 10^{-5} + \frac{\sum_{i=1}^{I} \sum_{t \in T_i} (B_i(t) - \sum_{k \in K} \gamma_k \beta_k X_{ki})^2}{2} \right).$$

2. Draw the random effects from

$$(34) \qquad p(\tau_n|\cdot) = N\left(\frac{N\theta_H \sum(\lambda_{in}(t) - f(t) - B_i(t))}{\theta_A + N\theta_H}, \theta_A + N\theta_H\right),$$

$$(35) \qquad p(B_i(t)|\cdot) = N(\mu_B, \theta_B + N\theta_H),$$

$$(36) \qquad \mu_B = \frac{\theta_B \sum \gamma_k X_k(t)\beta_k + I\theta_H \sum(\lambda_{in}(t) - f(t) - \tau_n)}{\theta_B + N\theta_H}.$$

3. Draw γ from

$$(37) \qquad \tilde{Y} = \begin{bmatrix} B_i(t) \\ 0 \end{bmatrix}, \qquad \tilde{X}_\gamma = \begin{bmatrix} X \\ D_\gamma R D_\gamma \end{bmatrix},$$

$$(38) \qquad S_\beta^2 = \tilde{Y}^T \tilde{Y} - \tilde{Y}^T \tilde{X}_\gamma (\tilde{X}_\gamma^T \tilde{X}_\gamma)^{-1} \tilde{X}_\gamma^T \tilde{Y},$$

$$(39) \qquad \begin{aligned} p(\gamma|\cdot) = |\tilde{X}_\gamma^T \tilde{X}_\gamma|^{-1/2} |D_\gamma R D_\gamma|^{-1/2} \\ \times (2 \cdot 10^{-5} S_\beta^2)^{-(\sum_{i=1}^I T_i + 10^{-5})/2} p(\gamma). \end{aligned}$$

4. Draw β from

$$(40) \qquad p(\beta|\cdot) = N\big((X^T X + D_\gamma R D_\gamma)^{-1} X B_i(t), (X^T X + D_\gamma R D_\gamma)^{-1}\big).$$

5. Draw $f(t)$ using the Bayesian adaptive regression splines algorithm described in Wallstrom, Liebner and Kass (2008).

6. Propose a new α_{in} from its prior distribution ($p(\alpha_{in}) \propto 1_{[Y_{in}(T_{in}), 1]}$) and use a Metropolis–Hastings step to compute the acceptance probability using the following likelihood:

$$(41) \qquad p(Y|\alpha_{in}, \cdot) \propto N\left[\frac{y_{in}(t)}{Y_{in}(t-1)} - \lambda_{in}(t)\left[1 - \frac{Y_{in}(t-1)}{M_i(t)\alpha_{in}}\right]\Big| 0, \theta_L\right].$$

7. Propose a new λ_{in} by adding white noise to the previous value. Use a Metropolis–Hastings step to calculate the acceptance probability using the following likelihood:

$$(42) \qquad \begin{aligned} p(\lambda_{in}(t)) &\propto N\left[\frac{y_{in}(t)}{Y_{in}(t-1)} - \lambda_{in}(t)\left[1 - \frac{Y_{in}(t-1)}{M_i(t)\alpha_{in}}\right]\Big| 0, \theta_L\right] \\ &\times N[\lambda_{in}(t) - f(t) - B_i(t) - \tau_n | 0, \theta_H] \\ &\times Ga(\lambda_{in}(t)|0.001, 1000). \end{aligned}$$

8. Repeat steps 1–7 until convergence.

SUPPLEMENTARY MATERIAL

R Code (DOI: 10.1214/11-AOAS519SUPP; .R). This supplement contains the R code from "Investigating International New Product Diffusion Speed: A Semiparametric Approach."

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