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## "Globalization": Modeling Technology Adoption Timing Across Countries

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# “Globalization”: Modeling Technology Adoption Timing Across Countries


### Abstract

Our paper proposes a general model of global adoption processes. In this case, the units of observation are countries which sequentially adopt a particular technology. We propose that the probability of a given country adopting a technology is a function of other “similar” countries having adopted earlier (i.e. reflecting endogenous factors, or “demonstration” effects), as well as a variety of country specific factors (exogenous covariates). We illustrate the approach using data from the cellular telephone industry for 184 countries. The findings generally support extant theories of cross-country adoption, whether generated by academicians or managers. In particular, we find that planned economies lag in adopting technologies, and that homogenous countries with a high level of economic development and population concentration are, on average, earlier adopters. Support is also found for the demonstration effect of earlier adoptions: the baseline hazard increases over time, and adoptions by countries significantly increase the likelihood of "similar" countries following their example.

# "Globalization": Modeling Technology Adoption Timing Across Countries

## 1. INTRODUCTION

Virtually every textbook on international or global management has a chapter on international segmentation strategies. The discussions in these focus on various criteria upon which managers can cluster countries into homogenous units within which uniform strategies can be developed. These criteria often involve economic, cultural, or social dispositions. Few, if any, consider the *dynamics of globalization* as a fundamental segmentation criterion. The globalization of any technology implies its *adoption* by the world's 184 countries located in Africa (55 countries), Asia (37 countries), Europe (32 countries), the Americas (45 countries) and other regions (15, mostly island, countries).[1] For any given technology, some of these countries will begin adopting sooner than others. In this paper, we explore the idea that countries can be characterized along the "innovator" to "laggard" spectrum in a similar way that consumers are classified for new product segmentation purposes (Robertson 1971). Of interest to international managers who face dynamic operational and/or resource allocation decisions or who have to establish strategic priorities, is a basic understanding of factors likely to affect the timing of a country "adopting", or allowing the importation of a given technology. In our paper, we seek to introduce a theoretical and modeling framework from which managers and academic researchers can better understand global adoption dynamics, and identify characteristics that can distinguish between countries which are, using Rogers' (1983) terminology, "innovators," "early adopters", "early majority", "late majority", or "laggards".

To illustrate the applied importance of this topic, consider Figure 1 which shows the aggregate adoption of cellular telephone service (subscriptions) on a worldwide basis. While one might be tempted to directly explain the dynamics of this aggregate diffusion pattern, this curve inherently masks an underlying process as yet unresearched in the literature: the breadth of adoption, or the variability in adoption timing across countries; i.e. when will each individual

[1] Countries are defined broadly, in that we also include territories, protectorates or colonies of United Nations members which are, however, often represented as being sovereign states in international agencies (e.g. the World Health Organization or the International Olympic Committee). These smaller states are generally autonomous, have disputed sovereignty, or are distant from the parent country (e.g. the Falkland Islands, Puerto Rico).

country first show, or allow, the sales of the technology? While *depth* processes (i.e. within-country diffusion dynamics given the adoption time) have been considered in other studies (e.g. Gatignon, Eliashberg and Robertson 1989; Takada and Jain, 1991; Helsen et al. 1993; Mahajan and Muller 1994), we focus on the breadth process which, of course, is a critical necessary condition to the depth process. Knowing that a country will have a large market potential and fast penetration rate may be inconsequential to planning if the country will only begin adoption well beyond the planning horizon (e.g., 10 to 15 years after the technology is originally introduced to the international community).

Over the past 30 years, the *management literature* has considered various aspects of technology diffusion. This literature has failed, however, to consider international breadth processes which, in contrast, have received substantial attention in other social-science disciplines. Table 1 presents a summary of an extensive cross-disciplinary review of the literature on the international diffusion of technologies. Based on a pool of over 6,000 diffusion studies across 16 social science disciplines, 77 studies were found to consider international diffusion. We have classified these studies as focusing either on the breadth or the depth dimension. The twelve studies dealing with depth processes generally compare and explain differences across within country diffusion patterns using a limited sample of countries; 6 studies in management (mostly in marketing), are of this kind. The vast majority of the 65 other studies (all in other social-science disciplines) consider breadth processes. The breadth studies are further classified, by discipline, into three distinct groups: (1) bilateral, (2) multinational, and (3) global. The 19 bilateral studies are limited in scope as they are concerned with diffusion occurring between two specific countries or geographic regions. In the economics literature, for example, authors are interested in understanding barriers to or policies affecting technology transfer between the United States and Japan, or from developed countries to underdeveloped countries. The 36 multinational studies consider the sequential diffusion across a small group of countries (e.g. the adoption of technology standards within the European community). The 10 global studies consider the entire community of nations, as in our study. All of these studies, however, are *qualitative* or *descriptive* discussions on international diffusion patterns (e.g. European countries seem to adopt technologies prior to African countries) or on international policies which stand to affect global diffusion (e.g. discussions on the impact of standard setting bodies, like the International Telecommunications Union).

To summarize, within the management literature, the breadth dimension of international diffusion has been completely ignored, and within the other social-science disciplines, global studies on the variability in adoption timing have been largely descriptive or qualitative in nature. Even though some of these studies have proposed theoretical arguments concerning the likely impact on a country's adoption timing of a variety of factors, none has formally modelled the process or empirically tested the resulting hypotheses. To supplement the cross-disciplinary international diffusion literature in general and the international management literature in particular, we propose in Section 2 a formal modeling approach which can be used to test a variety of international diffusion theories (e.g. Gatignon and Robertson 1985; Rogers 1983). In Section 3, we apply the model to an illustrative example, the cellular telephone industry, and conclude in Section 4 with a discussion on implementation issues, managerial implications, and areas for future research.

## 2. A GLOBAL ADOPTION MODEL

### 2.1 Introduction

Since the 1960s, several aggregate diffusion models have been developed and documented in the literature which are specifically designed to evaluate technology acceptance over time (see the reviews in Bridges, Coughlan and Kalish 1991; Lilien, Kotler and Moorthy 1992; Mahajan, Muller and Bass 1990; Parker 1994; Simon 1989). While aggregate diffusion models are well suited to study the depth of adoption for one product in one country, they are not very useful to explain the breadth of technology adoption across countries.

Consider, for example, Figure 2 which shows both the actual number of countries introducing cellular services in a given year and the number of adopters predicted by the aggregate diffusion model of Easingwood, Mahajan and Muller (1983). Even though this model gives a parsimonious description of how fast the technology will be accepted across the world, it does not help management to understand why certain countries adopt sooner than others. Indeed, aggregate diffusion models treat each country as a homogenous unit, and cannot explain why some countries have a higher probability of adopting in a given year than others. Micro-level models relax this homogeneity assumption, and allow the probability of adoption to be heterogeneous across potential adopters (Chatterjee and Eliashberg 1990; Sinha and Chandrashekaran 1992). Moreover, since the unit of analysis is at the individual level, various causal factors which may affect the individual adoption decision can be included into the model and formally tested. Hannan and

McDowell (1984), Sharma (1993), Sharma and Sinha (1991a) and Sinha and Chandrashekaran (1992), for example, all investigated the impact of firm and market characteristics on the adoption timing of automated teller machines.

Conceptually, we extend these approaches to international diffusion processes where our units of observation are countries rather than firms. Methodologically, our model will have a number of advantages over the aforementioned studies. We will use a flexible hazard model which: (1) adjusts for the grouped nature of the data, (2) assumes no distributional assumptions with respect to the form of the baseline hazard, (3) incorporates both time-invariant and time-varying covariates, (4) corrects for unobserved heterogeneity, and (5) explicitly tests the managerial assumption that eventually all countries will adopt the technology. While each of these individual features has been applied before in the literature (see e.g. Helsen and Schmittlein 1993; Jain and Vilcassim 1991; Sharma 1993; Sinha and Chandrashekaran 1992), our study is the first to incorporate all of them simultaneously.

## 2.2 The Model

Let $T$ denote the random duration until a country adopts the technology with probability density function $f(t)$, cumulative distribution function $F(t)$ and hazard function $\lambda(t)$. Yearly grouping intervals $[t_{k-1}, t_k)$, $k = 1, 2, ..., m+1$, $t_0 = 0$ and $t_{m+1} = \infty$ are defined, and adoption in duration interval $[t_{k-1},t_k)$ is recorded as $t_k$. It should be emphasized that $t_k$ does not refer to actual calendar time, but to the number of years elapsed since the system first became available. Cellular technology, for example, was first tried (but not adopted) on a limited scale by the government of Qatar in June 1979, which becomes the starting point of our time axis. Japan introduced the technology by the end of 1979, and is therefore given a duration of one (i.e. they adopted within the first year the technology was available), while France adopted in 1985, the seventh year.[2] For those countries which had not yet adopted a cellular system by September 1990 (the right-censored observations), a duration of 12 years is recorded.[3]

[2] For 87% of the adopting countries, we know both the year and month of adoption so that we can easily calculate the associated grouping interval (e.g. France adopted in November 1985, i.e. after 78 months, and is assigned to the seventh grouping interval). For 13% of the adopting countries, only the year of adoption is known, and for those countries we assume that adoption occurred in the middle of the year (June). None of our substantive results was affected, however, when we assumed that adoption occurred at the beginning or end of the year.

[3] The end of the observation period is September 1990. This enables us to clearly distinguish communist from non-communist countries, a distinction which became blurred after the Fall of the Berlin Wall. Going

Parameter estimates are obtained through maximum-likelihood estimation, and the contribution to the likelihood function differs depending on whether or not a country has adopted cellular technology by the end of the observation period. The contribution to the likelihood function of country $k$ which adopted the technology in year $t_k$ is given by $S(t_k\text{-}1)\text{-}S(t_k)$, where the survivor function $S(t_k) = 1\text{-}F(t_k)$ denotes the probability that the country has not yet adopted the new technology after $t_k$ years. By working with the difference of survivor functions rather than with the density function, we recognize the discrete nature of the yearly duration intervals. This adjustment is needed since not accounting for the discrete nature of the data has been shown to result in inconsistent parameter estimates, with increasing asymptotic bias as the grouping becomes more coarse (Kiefer 1988; Sharma and Sinha 1991a,b).[4] For country $l$ which has not yet adopted cellular systems by September 1990, the contribution to the likelihood function is given by $S(t_l\text{-}1)$, i.e. we assume that censoring takes place at the beginning of the duration interval. Clearly, some such assumption is required given the grouping in the data. The contribution to the likelihood function of any country $i$ can therefore be written as:

$$L_i(t_i) = [S(t_i - 1) - S(t_i)]^{1-d_i} \, [S(t_i - 1)]^{d_i} \; , \tag{1}$$

where $d_i$ is an indicator variable which takes the value of one if the country has not yet adopted by the end of September 1990, and zero otherwise; as such, all 184 countries, whether they have adopted or not, are contributing to the likelihood function.

To incorporate covariates into the model, we first propose an expression for the hazard function, and subsequently use a general relationship between a distribution's hazard and survivor function. We write the hazard function $\lambda_i(t)$, which gives the adoption rate of country $i$ in duration interval $t$ as:

$$\lambda_i(t) = \lambda_0 \; e^{\beta \, X_i(t)} \; e^{c \, D_i(t)} \; . \tag{2}$$

This expression consists of three building blocks. First, $\lambda_0$ gives the adoption rate of countries in the base group in the first year after the technology's introduction. The base group is defined as

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beyond September 1990 would also have affected the sample size in that the national boundaries of a number of countries have changed.

[4] As such, not adjusting for the discrete nature of the data may be fairly inconsequential when working with daily or weekly data (e.g. Jain and Vilcassim 1991), but may seriously affect the parameter estimates when working with annual grouping intervals (e.g. Sinha and Chandrashekaran 1992).

those countries for which all covariates, given by the vector $X_i(t)$, are zero. Second, when some of the covariates are different from zero, the country's hazard is multiplied by $\exp[\beta\ X_i(t)]$. A positive $\beta$ coefficient implies that an increase in the value of the associated covariate augments the (conditional) adoption probability, or conversely, reduces the expected time until adoption.[5] Finally, a set of time-varying dummy variables $D_i(t)$ is added to capture a wide variety of time dependencies. Consider, for example, the situation where a separate dummy is included for every possible adoption year. The time-varying dummy associated with year three is always zero, except during year three when it takes the value of one, i.e. its different values are (0 0 1 0 ...). To avoid identification problems when simultaneously estimating $c_1$ and $\lambda_0$, no dummy variable is included for the first year. As such, $\lambda_0$ reflects the adoption rate of the base group in the first period, and positive (negative) $c$-coefficients for the other intervals indicate a higher (lower) adoption rate compared to that first year. This approach makes no distributional assumption with respect to the nature of the time dependence, and is therefore called non-parametric (Vanhuele et al. 1995). The only assumption made is that within a grouping interval (e.g. a year) the hazard remains constant. Intuitively, this is equivalent to a piece-wise approximation of an underlying, possibly very complex, continuous time-dependence pattern. Its main advantage is that it results in consistent parameter estimates even when the true form of the baseline is unknown. In contrast, an incorrect parametric specification results in inconsistent parameter estimates (Meyer 1990). Because of the variability in the observed durations (ranging from one to twelve years), the small number of adopting countries (63), and the need to have a sufficient number of adoptions in any given period to reliably estimate the associated $c$-parameter, we limit in our empirical application the number of discrete jumps in the baseline hazard. Rather than allowing for a different $c$-parameter in every year, we allow for a discrete shift after every three years.[6]

To estimate the parameters of interest, an expression for the survivor function $S_i(t)$ associated with the hazard in (2) is needed. It can be shown (see e.g. Lancaster 1990) that:

$$S_i(t) = e^{-\int_0^t \lambda_i(u)du} . \tag{3}$$

When the time-varying covariates are assumed to remain constant within a given year, but are allowed to vary from year to year, (3) can be written as (Gupta 1991, Vanhuele et al. 1995):

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[5] Specifically, when the $j$-th covariate changes by one unit, the hazard changes by $[\exp(\beta_j)-1)]*100$ percent.

[6] Our substantive findings were not affected by this choice, and similar results were obtained when working with shifts after two or four years.

$$S_i(t) \;=\; e^{-\lambda_0 B_i(t)}, \text{ where } B_i(t) \;=\; \textstyle\sum_{j=1}^{t} e^{\beta X_i(j) + c D_i(j)} . \tag{4}$$

After appropriate substitutions, the log-likelihood function for *N* countries becomes:

$$LL \;=\; \textstyle\sum_{i=1}^{N} \{(1 - d_i) \log[e^{-\lambda_0 B_i(t_i-1)} - e^{-\lambda_0 B_i(t_i)}] - d_i \;\lambda_0\; B_i(t_i - 1)\} . \tag{5}$$

In Equation (5), we basically assume that every country in the base group has the same initial adoption probability $\lambda_0$. However, some of the factors that can have an impact on a country's adoption timing may be hard to quantify (e.g. the attitude of its political leaders towards technologies), or may not have been available in our data set (e.g. the number of political parties forming the government at any given point in time). Not accounting for these omitted factors (often referred to as unobserved heterogeneity) has been shown to cause a spurious negative duration dependence (as reflected in a downward bias on the *c*-coefficients), and to result in inconsistent parameter estimates for the included covariates (see e.g. Lancaster 1990). To correct for the presence of unobserved heterogeneity, we let $\lambda_0$ be distributed according to a gamma mixing distribution.[7] This mixing distribution is quite flexible, and has been shown to result in the closed-form solution for the likelihood function given in Equation (6) (see Vanhuele et al. 1995 for a formal proof):

$$LL = \textstyle\sum_{i=1}^{N} \ln\{(1 + d_i) \left[\frac{a}{B_i(t_i - 1) + a}\right]^r - \left[\frac{a}{B_i(t_i - 1) + (1 - d_i)\; e^{\beta X_i(t_i) + c D_i(t_i)} + a}\right]^r\}. \tag{6}$$

The average first-year adoption rate for countries in the base group is then given by the mean of the mixing distribution, *r/a*, and all other coefficients can be interpreted relative to this ratio in the same way as they were interpreted vis-à-vis $\lambda_0$ in earlier models.

Finally, to explicitly allow for the fact that some countries may never adopt cellular technology, we extend the model in Equation (6) using the homogenous split-hazard approach of Sinha and Chandrashekaran (1992). Intuitively, this approach allows for a discrete spike at $\lambda_0 = 0$.

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[7] The gamma mixing distribution is also used in Dekimpe and Morrison (1991), Gupta (1991), Han and Hausman (1990), Meyer (1990) and Sharma and Sinha (1991a,b), among others. Other authors (e.g. Jain and Vilcassim 1991, Vilcassim and Jain 1991) have modeled the baseline hazard parametrically and the unobserved heterogeneity non-parametrically. This was motivated by the findings of Flinn and Heckman (1982) and Heckman and Singer (1984) that for a given parametric form of the baseline, the results tend to be very sensitive to the form of the mixing distribution. Recent research has shown, however, that the specification of the heterogeneity component is not as crucial as a flexible specification of the time dependence (Han and Hausman 1990; Manton, Vaupel and Stallard 1986; Ridder 1986).

The magnitude of this spike allows us to test the managerial intuition that in the long run all countries will adopt the technology. Following Sinha and Chandrashekaran (1992), we define an indicator variable $A_i$, where $A_i$ is equal to one if the country belongs to the group of eventual adopters, and zero otherwise. If the probability of $A_i$=1 (denoted as $\delta_i$) is assumed to be homogeneous across all countries (i.e. $\delta_i$=$\delta$), it can be interpreted as the fraction of countries that will adopt in the long run. A likelihood-ratio test can subsequently be used to test the managerial intuition that $\delta$ is equal to one in the cellular-telephone industry.

Using a similar logic as in Sinha and Chandrashekaran, but making an adjustment for the discrete nature of the data, it is easy to show that the likelihood function for $N$ countries is given by:

$$L = \Pi_{i=1}^{N} \{\delta\,[S_i(t_i - 1) - S_i(t_i)]\}^{1-d_i} * \{(1 - \delta) + \delta\, S_i(t_i - 1)\}^{d_i} . \qquad (7)$$

If all countries which will eventually adopt have the same $\lambda_0$, one can substitute equation (4) into (7) to derive a split hazard model which does not yet correct for unobserved heterogeneity among the eventual adopters. In order to account for this heterogeneity, one can again let $\lambda_0$ be distributed according to a gamma mixing distribution. After lengthy derivations, the following expression for the log-likelihood function is obtained (see Van de Gucht 1994):

$$LL = \sum_{i=1}^{N} \ln \{ \frac{(\delta^{1-d_i} - \delta)(1+d_i)\, a^r}{[(1-d_i)\, B_i(t_i - 1) + a]^r} - \frac{(\delta^{1-d_i} - \delta)\, a^r}{[(1-d_i)\, B_i(t_i) + a]^r} + \frac{\delta(1+d_i)\, a^r}{[B_i(t_i - 1) + a]^r} - \frac{\delta\, a^r}{[B_i(t_i - 1) + (1-d_i)\, e^{\beta X_i(t_i)+cD_i(t_i)} + a]^r} \}, \qquad (8)$$

where all variables are defined as before.

An alternative way to allow for the possibility that adoption will never take place for some countries is to work with a degenerate parametric density function, such as the Inverse Gaussian, to describe the baseline hazard. In those instances, $\lim_{t\to\infty} S(t)>0$ (see Lancaster 1990). This offers less flexibility in modeling various forms of time dependence, however, does not ensure the consistency of the parameter estimates (as the a priori parametric form may be incorrect), and does not allow to characterize which countries are most likely to never adopt. When working with the split-hazard specification, on the other hand, one may replace $\delta$ by $\delta_i$ in (8), where

$$\delta_i = \frac{1}{[1+\exp(\alpha X_i)]} \qquad (9)$$

to determine what covariates affect the probability of belonging to the group of potential adopters when $\delta<1$ (see Sinha and Chandrashekaran 1992 for a marketing application).

The model in Equation (8) extends Sinha and Chandrashekaran's work in three different ways, since they (1) specified the baseline hazard parametrically (as opposed to our non-parametric specification), (2) made no adjustment for the discrete nature of the data (even though they also worked with yearly data intervals), and (3) did not make a correction for unobserved heterogeneity. As indicated before, each of these issues may have affected the consistency of their parameter estimates. A more complete comparison of the proposed model specification with earlier applications of hazard-rate models is given in Table 2. This table illustrates that our model is the first to integrate all aforementioned properties.

## 3. EMPIRICAL ILLUSTRATION

### 3.1 The Data

We now turn to an empirical illustration of the model using data collected from the cellular telephone industry -- an industry having undergone a global adoption process. Data on the cross-country adoption timing in the cellular telephone industry were collected from the relevant government agencies, trade associations, and the International Telecommunications Union, a United Nations Agency.[8] Based on these sources, Table 3 classifies countries along the "innovator-laggard" spectrum proposed by Rogers (1983), whereby late majority and laggard countries are those which had yet to offer service in 1993.

To assess the impact of both endogenous and exogenous forces on this classification, data were collected on factors which have been described in the extant literature as being likely to affect cross-country adoption processes. First, we consider the importance of the endogenous demonstration effect exerted by earlier adoptions in "similar" countries. Gatignon and Robertson (1985, p. 858) suggest that "social similari[ties] between the countries are negatively related to the diffusion sequence across countries." To capture the impact of previous adoptions by "similar" countries, a time-varying covariate is added which measures how many nations in a country's "World-Bank group" have adopted cellular technology by the end of the previous grouping

[8] The innovation is defined as "mobile cellular-like telecommunications subscriptions" (as opposed to a particular type of terminal equipment).

interval.[9] The World Bank defines nine categories of countries which are similar in terms of a number of socioeconomic and political variables; 156 countries fit into one of these categories. Rather than combining the remaining 28 countries in an "others" category (which would imply considering Cuba and Monaco as similar countries), we will test the impact of this endogenous factor on the more restricted data set of 156 countries. Countries also have political and economic ties with countries outside their World-Bank group. The demonstration effect from adoptions in those countries will be reflected in the baseline hazard, which is therefore expected to increase over time (Helsen and Schmittlein 1993; Sharma and Sinha 1991a). We also consider the following exogenous forces motivated in the literature, discussed below: political disposition (communist or not), socioeconomic characteristics (GNP per capita, crude death rate, population growth), social-system homogeneity (number of ethnic groups) and population concentration (number of major population centers). The data covering these covariates were collected from Euromonitor Ltd. and the *World Factbook* (Central Intelligence Agency, 1993). Relevant summary statistics are presented in Table 4.[10] The highest correlation between the respective variables does not exceed 0.4, suggesting that multicollinearity is not a problem.

### 3.2 Estimation and Hypothesis Testing

Parameter estimates for a number of different model specifications are given in Table 5. In Table 5, we impose the managerial assumption that all countries will eventually adopt; we will test that assumption later on. The first column of Table 5 presents the estimates for a model which explicitly accounts for unobserved heterogeneity (Eq. 6), but which does not yet include the time-varying proportion of earlier adoptions in a country's World-Bank group. It is found that non-communist countries, with a high GNP per Capita, a low crude death rate, few ethnic groups and many major population centers tend to be early adopters of cellular technology. Most estimates have the signs that could be expected on the basis of diffusion theory and/or managerial intuition for this technology. The diffusion literature has argued that a society's adoption timing is related to its standard of living and stage of economic development (Antonelli 1993; Gatignon and Robertson 1989), for which gross national product (wealth) and crude death rate (poverty) are main indicators

[9] Since June 1979 is the start of our time axis, we computed the percentage of adopters in each World-Bank category in May 1980, May 1981, etc. Percentages are used to correct for the fact that not all groups have the same number of countries.

[10] As data on 184 countries are difficult to collect on a year-to-year basis, we treat the exogenous covariates as time-invariant, i.e. we assume that they did not vary in a systematic fashion over the considered time span.

(Helsen et al. 1993). Similarly, several case studies have shown that the planned economies of the Soviet Union and Eastern Europe tend to lag in the adoption of new technologies (see e.g. Amann and Cooper 1982; Berliner 1976; Leary and Thornton 1989). With respect to the negative impact of the number of ethnic groups, Gatignon and Robertson (1985) argue that homogenous social systems (for which we use the number of ethnic groups as a proxy) tend to be characterized by faster (and in our case, earlier) diffusion rates. Several managers in the industry argue that the relative advantage of cellular phone systems over existing technologies is directly related to the number of urban areas or major population centers, which explains the positive parameter estimate for this covariate. Population growth (a surrogate for the need to expand the telecommunications infrastructure), on the other hand, had no significant impact on the countries' adoption timing.

The increasing baseline hazard in this model captures the "demonstration" (Mansfield 1968, Sharma and Sinha 1991a) or "snowball" (Helsen and Schmittlein 1993) effect resulting from previous adoptions within *and* outside a country's World-Bank group: as more countries have adopted the technology, the uncertainty surrounding its value diminishes since potential adopters can benefit from the experience of the earlier adopters.

In Model 2, no adjustment for unobserved heterogeneity is made. Even though the signs of the respective coefficients are not affected, we see that the magnitude of the parameter estimates is somewhat larger when this correction is made. Accounting for unobserved heterogeneity therefore seems to eliminate (some of) the attenuating effects of the omitted variables. Note in this respect that the number of ethnic groups in the country only has a significant impact when correcting for unobserved heterogeneity. Also the demonstration effect is much more pronounced in Model 1, since the downward bias caused by the spurious aggregation effect has been reduced by adding the gamma mixing distribution. This phenomenon is illustrated further in Figure 3 where we use the parameter estimates from Model 1 and 2 to derive the hazard rate for an "average" non-communist country.

To obtain further insights into the relative importance of the demonstration effect, we explicitly account for the proportion of previous, similar adopters in Model 4. As indicated before, the World-bank classification which is used as a measure of similarity is only available for 156 countries. To enhance the comparability with the previous models, we re-estimated Model 1 on this restricted sample (see Model 3 in Table 5), and found the results to be very similar across the two samples. The main difference appears in the initial base hazard ($r/\alpha$) which becomes larger when estimated on 156 countries. Some face validity for this result is obtained when noting that only 7 of the omitted countries had adopted the technology, and that those seven all did so shortly before the end of the observation period. Put differently, they appear to have been "lagging" in their adoption decision, and their omission from the sample caused an increase in the average hazard for the remaining countries. Consistent with the hypothesis that there is a strong demonstration effect among "similar" countries, a significant positive parameter estimate is obtained. In terms of the economic significance of the estimate, a country's hazard in any given year is 43.1 (104.7) percent higher when one fourth (half) of the countries in its World-Bank group have adopted the technology than if none had done so. Also, the baseline hazard in Model 4 only reflects the demonstration effect by non-member countries, and is not as steep as in Model 3.

Finally, we estimated a split-hazard model (both with and without gamma mixing distribution) to test whether, as managers in the industry expect, all 156 countries will eventually adopt. The parameter estimate for the proportion of ultimate adopters (the parameter $\delta$) converged to one in both cases, and for the split-hazard model with unobserved-heterogeneity correction, the same parameter estimates as in Model 4 were obtained. As such, in the long run, all countries will likely adopt cellular-telephone networks.

Summarizing this illustrative study, we have relaxed the homogeneity assumption common to aggregate diffusion models, and assessed which covariates affect a country's adoption timing. In addition to demonstrating the approach's flexibility to incorporate theoretical paradigms, our particular application indicates that planned economies lag in allowing technologies, and that homogenous countries with a high level of economic development and population concentration are, on average, earlier adopters. Support was also found for the demonstration effect of earlier adoptions: the baseline hazard increases over time, and adoptions by countries significantly increase the likelihood of "similar" countries adopting (World Bank group members). Moreover, we provided empirical support for the managerial intuition that eventually all countries will adopt cellular technology.

## 4. CONCLUDING REMARKS

This paper studied global adoption processes, or the timing of initial adoption at the country level (breadth). We illustrated the application of our approach to the global adoption of cellular telephone systems across 184 countries.

### 4.1. Pragmatic Considerations

Our approach allows researchers to rigorously test a number of hypotheses/theories, whether generated by the academic community, managers, or economic planners. There are, however, a number of pragmatic issues associated with generating and testing international theories of diffusion which should be kept in mind. First, specific theories or hypotheses ultimately depend on the category under consideration, even though general diffusion and economic theories can offer the overall framework. For example, in their study of cross-European diffusion patterns for household appliances, Gatignon et al. (1989) propose that diffusion patterns for time-saving technologies are a function of the country's sex roles, or the percentage of women in the labor force. While this might appear plausible for dishwashers and deep freezers, it is not clear that this proposition is (or should be) a useful hypothesis for all technologies (e.g. nuclear submarines). As such, we do not claim that the covariates included in our study should be equally relevant for all other technologies. Our empirical results should be interpreted as an illustration of how a variety of hypotheses can be tested rigorously, rather than as empirical generalizations. Second, a practical problem in testing "global theories" is the need to use globally representative proxies. As applied international researchers are well aware, the requirement to use covariates which measure international differences across 184 countries leaves us with a limited set of variables (e.g. basic socioeconomic characteristics). As a consequence, some of the factors which could potentially have an impact on, say, the adoption timing were not included in the model because their values were only available for a small fraction of the countries,[11] and also the development of multi-item scales was infeasible.

### 4.2. Extensions

While the modeling approach suggested is quite general, we have illustrated it on an industry undergoing a *decentralized* process. Indeed, the manufacturers themselves did not determine when sales would begin in a specific country. Instead, local governments determined from what point in time the technology was allowed to be introduced in their country. Such processes are likely to exist for a wide variety of technologies or products such as most medical

[11] As indicated before, this makes a correction for unobserved heterogeneity an important property of our hazard specification.

products, telecommunication services, energy-supply systems, electronic products which must meet local type approval, cosmetics, or any other packaged consumer goods which require government approval or face non-tariff barriers. For other industries, global cross-country diffusion may be the result of what Rogers (1983) calls a *centralized* process whereby the firm (i.e. the change agent) systematically determines where the technology should be sold next. When firms themselves plan the introduction sequence (i.e. when dealing with centralized processes), one can still use the proposed modeling techniques as research tools, though the nature of the explanatory variables may be somewhat different. Clearly, the use of the proposed modeling approach should be extended to such processes.

Finally, we have applied the model to a typical "high technology" industry. Future research is warranted on generating empirical generalizations with respect to cross-country adoption patterns. Do most categories undergo international diffusion patterns? Are the "innovative" countries similar across categories (similarly for the other categories of adopters identified by Rogers)? If there is variance across categories, what factors explain these differences? We leave these questions to future research.

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**Table 1. Cross-Disciplinary Summary of International Studies of Technology Diffusion**

| Discipline | Depth Studies | Breadth Studies | | |
|---|---|---|---|---|
| | | Bilateral | Multinational | Global |
| Biotechnology | | 1 | | |
| Demography | | | 1 | |
| Development Economics | | 7 | 7 | 1 |
| Ecology | | 1 | | |
| Economic History | | 2 | 2 | 6 |
| Economics | 4 | 1 | 14 | |
| Forecasting | | | 1 | |
| Geography | | 1 | | |
| Industrial Economics | 1 | 2 | 2 | 1 |
| Law | | | 1 | |
| Management | 6 | | | |
| Political Science | | 2 | 1 | 2 |
| Public Health | 1 | 2 | 6 | |
| Urban Studies | | | 1 | |
| **Total** | **12** | **19** | **36** | **10** |

Note: Details on the included studies are available from the authors upon request.

**Table 2. Summary of Hazard-rate Models in Marketing**

| Study | Covariates | Correction for Grouped Nature | Nonparametric Baseline Hazard | Unobserved Heterogeneity | Split Hazard |
|---|---|---|---|---|---|
| Dekimpe and Morrison (1991) | No | Yes | No | Gamma | No |
| Gönül and Srinivasan (1993) | Yes | No | Yes | Fixed effects/ Gamma | No |
| Gupta (1991) | Yes | No | No | Gamma | No |
| Hannan and McDowell (1984) | Yes | Yes | No | No | No |
| Jain and Vilcassim (1991) | Yes | No | No | Normal/ Nonparametric | No |
| Sharma (1993) | Yes | Yes | Yes | Gamma | No |
| Sharma and Sinha (1991 a, b) | Yes | Yes | Yes | Gamma | No |
| Sinha and Chandrashekaran (1992) | Yes | No | No | No | Yes |
| Helsen and Schmittlein (1993) | Yes | No | No | No | No |
| Helsen and Schmittlein (1994) | Yes | No | No | No | No |
| Vilcassim and Jain (1991) | Yes | No | No | Nonparametric | No |
| **Present Study** | Yes | Yes | Yes | Gamma | Yes |

## Table 3. Diffusion of Cellular Services Across Countries

| Innovator (4%) | Early Adopter (12%) | Early Majority (33%) | Late Majority and Laggards (51%) | |
|---|---|---|---|---|
| Denmark | Australia | Algeria | Afghanistan | Malawi |
| Finland | Austria | American Samoa | Albania | Maldives |
| Indonesia | Bahrain | Argentina | Andorra | Mali |
| Japan | Canada | Bahamas | Angola | Martinique |
| Norway | France | Bangladesh | Antigua & Barbuda | Mauritania |
| Saudi Arabia | Germany (west) | Belgium | Barbados | Monaco |
| Spain | Iceland | Bermuda | Belize | Mongolia |
| Sweden | Ireland, Republic of | Bolivia | Benin | Mozambique |
| | Israel | Botswana | Bhutan | Namibia |
| | Italy | Brazil | Burkina Faso | Nauru |
| | Kuwait | Brunei | Burma | Nepal |
| | Luxembourg | Bulgaria | Burundi | Netherlands Antilles |
| | Malaysia | Cayman Islands | Cambodia | New Caledonia |
| | Netherlands | Chile | Cameroon | Nicaragua |
| | Oman | China, People's Rep | Cape Verde | Niger |
| | South Africa | Colombia | Central African Rep | Papua New Guinea |
| | South Korea | Costa Rica | Chad | Puerto Rico |
| | Thailand | Cyprus | Comoros | Qatar |
| | Tunisia | Czechoslovakia | Congo | Reunion |
| | Turkey | Dominican Republic | Cote D'Ivoire | Rwanda |
| | United Kingdom | Ecuador | Cuba | Sahara, Western |
| | United States | Egypt | Djibouti | San Marino |
| | | El Salvador | Dominica | Sao Tome E Principe |
| | | Fiji | East Germany | Senegal |
| | | Gabon | Equatorial Guinea | Seychelles |
| | | Ghana | Ethiopia | Sierra Leone |
| | | Greece | Falkland Islands | Solomon Islands |
| | | Guatemala | French Guiana | Somalia |
| | | Honduras | French Polynesia | St. Lucia |
| | | Hungary | Greenland | St. Vincent & the Gr |
| | | India | Grenada | Sudan |
| | | Kenya | Guadeloupe | Suriname |
| | | Laos | Guam | Swaziland |
| | | Lebanon | Guinea | Syrian Arab Republic |
| | | Macau | Guinea-Bissau | Tanzania |
| | | Malta | Guyana | The Gambia |
| | | Mauritius | Haiti | Togo |
| | | Mexico | Iran, I.R. of | Tuvalu |
| | | Morocco | Iraq | Uganda |
| | | New Zealand | Jamaica | United Arab Emirates |
| | | Nigeria | Jordan | USSR (Former) |
| | | Pakistan | Kiribati | Vanuatu |
| | | Panama | Lesotho | Virgin Islands, US |
| | | Paraguay | Liberia | Western Samoa |
| | | Peru | Libya | Yugoslavia |
| | | Philippines | Liechtenstein | Zambia |
| | | Poland | Madagascar | Zimbabwe |
| | | Portugal | | |
| | | Romania | | |
| | | Singapore | | |
| | | Sri Lanka | | |
| | | St. Kitts and Nevis | | |
| | | Switzerland | | |
| | | Taiwan | | |
| | | Tonga | | |
| | | Trinidad & Tobago | | |
| | | Uruguay | | |
| | | Venezuela | | |
| | | Vietnam | | |
| | | Zaire | | |

Time

**Table 4. Summary Descriptive Statistics of Exogenous Covariates (N = 184 countries)**

| Covariate | Means | STDV | Min. | Max. |
|---|---|---|---|---|
| **Demographic Factors** | | | | |
| Avg. Annual Pop. Growth Rate | 2.0 | 1.3 | -0.6 | 6.3 |
| No. of Major Population Centers | 8.0 | 4.0 | 1.0 | 19.0 |
| **Economic Factors** | | | | |
| GNP per Capita ($000) | 5,065.0 | 7,488.0 | 71.0 | 50,000.0 |
| Crude Death Rate | 9.4 | 4.4 | 2.0 | 23.0 |
| Communism | 0.1 | 0.3 | 0.0 | 1.0 |
| **Social System Factors** | | | | |
| No. of Ethnic Groups | 5.0 | 2.6 | 1.0 | 15.0 |

**Table 5. Parameter estimates for the cross-country timing model**

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $\lambda_0$ | – | 0.005 | – | – |
| $r/a$ | 0.002 | - | 0.007 | 0.012 |
| **Time Dependence** | | | | |
| $c_2$ (4-6 yrs) | 1.071* | 0.709 | 0.732 | 0.457 |
| $c_3$ (7-9 yrs) | 2.909*** | 2.044*** | 2.429*** | 1.912*** |
| $c_4$ (10-12 yrs) | 4.224*** | 2.814*** | 3.561*** | 2.980*** |
| **Exogenous Factors** | | | | |
| **Demographic Factors** | | | | |
| Avg. Annual Pop. Growth Rate | -0.082 | -0.112 | -0.235 | -0.242 |
| No. of Major Population Centers | 0.266*** | 0.208*** | 0.199*** | 0.180*** |
| **Economic Factors** | | | | |
| GNP per Capita ($10,000,000) | 1.160*** | 0.580*** | 1.073*** | 0.872*** |
| Crude Death Rate | -0.169** | -0.147** | -0.172** | -0.174** |
| Communism | -2.781* | -2.423*** | -2.520*** | -2.237** |
| **Social System Factors** | | | | |
| No. of Ethnic Groups | -0.209* | -0.095 | -0.196* | -0.181* |
| **Endogenous Factors** | | | | |
| Proportion of World Bank | - | - | - | 1.433* |
| N | 184 | 184 | 156 | 156 |
| Log likelihood | -206.73 | -210.74 | -166.53 | -164.70 |
| AIC [(-2LL) + 2(# parms)] | 435.46 | 441.48 | 355.06 | 353.40 |

**Note:** * < 0.1, ** . 0.01, *** , 0.001
Model 1: 184 countries - only exogenous covariate - with gamma mixing
Model 2: 184 countries - only exogenous covariate - without gamma mixing
Model 3: 156 countries - only exogenous covariate - with gamma mixing
Model 4: 156 countries - exogenous and endogenous covariate - with gamma mixing

**Figure 1. Worldwide Adoption of Cellular Subscriptions**

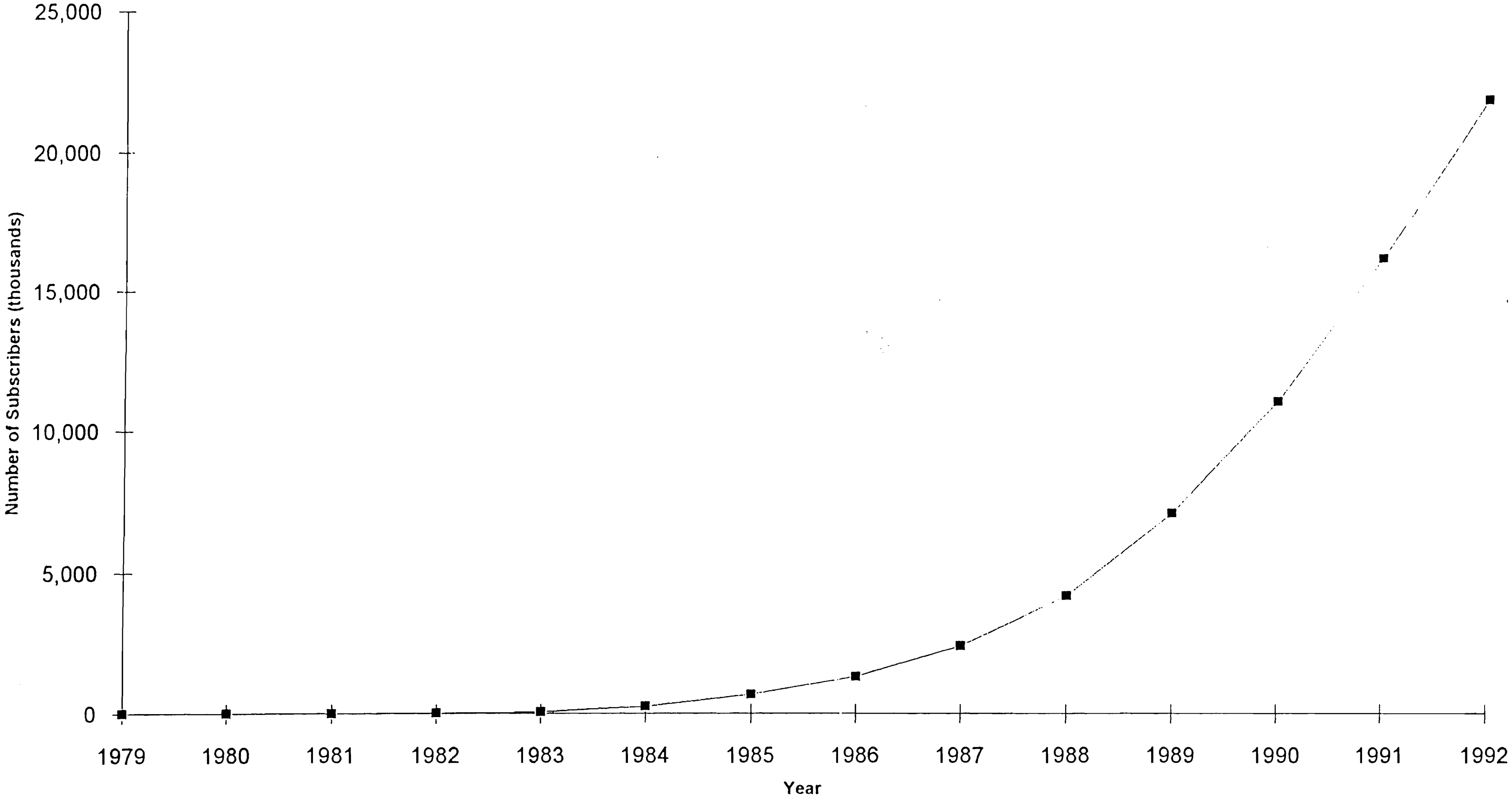
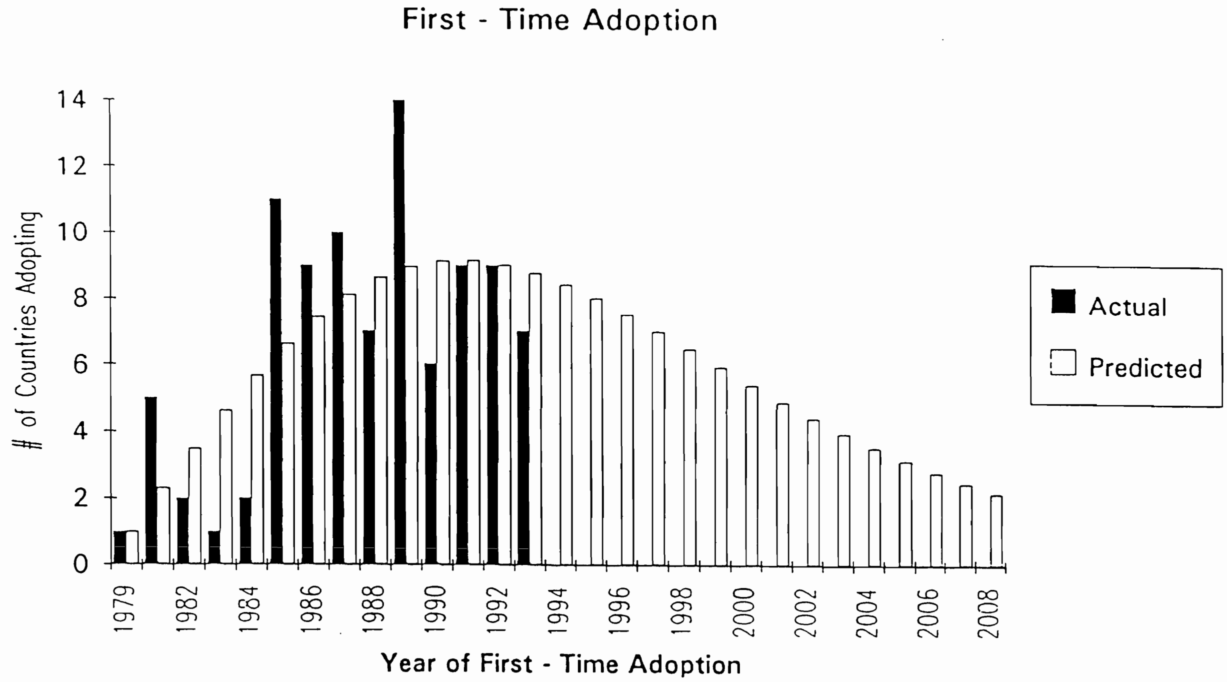


**Figure 2. Country Adoption of Cellular Telephone Systems**



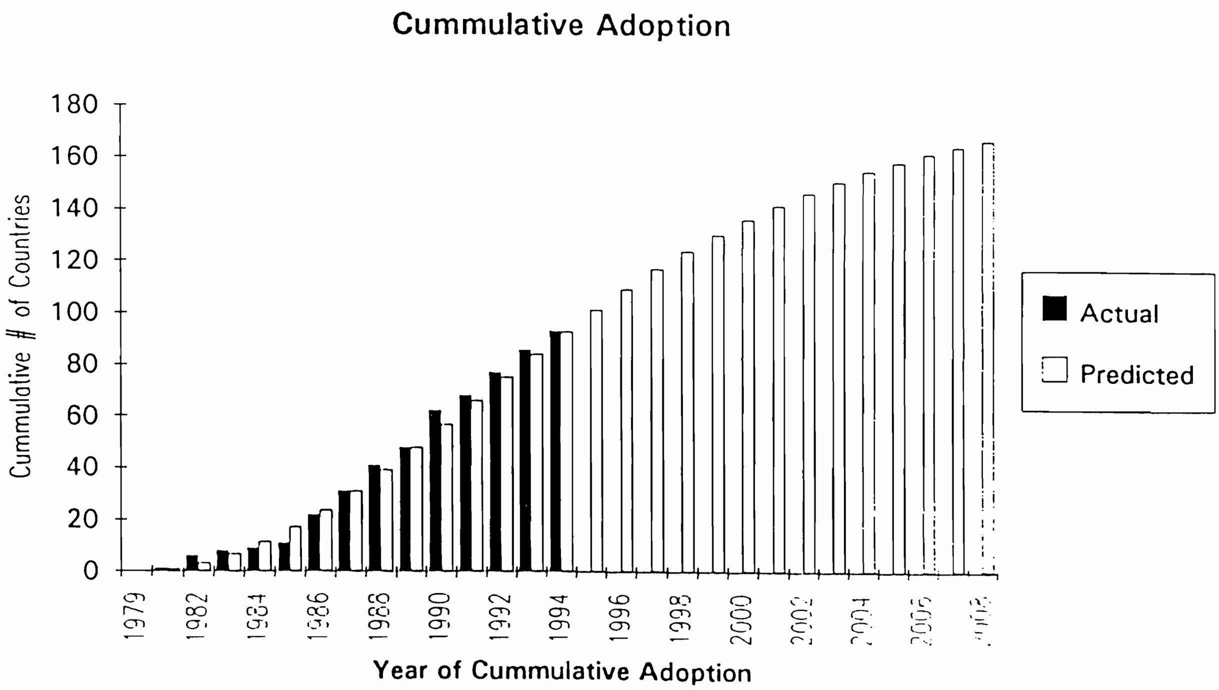
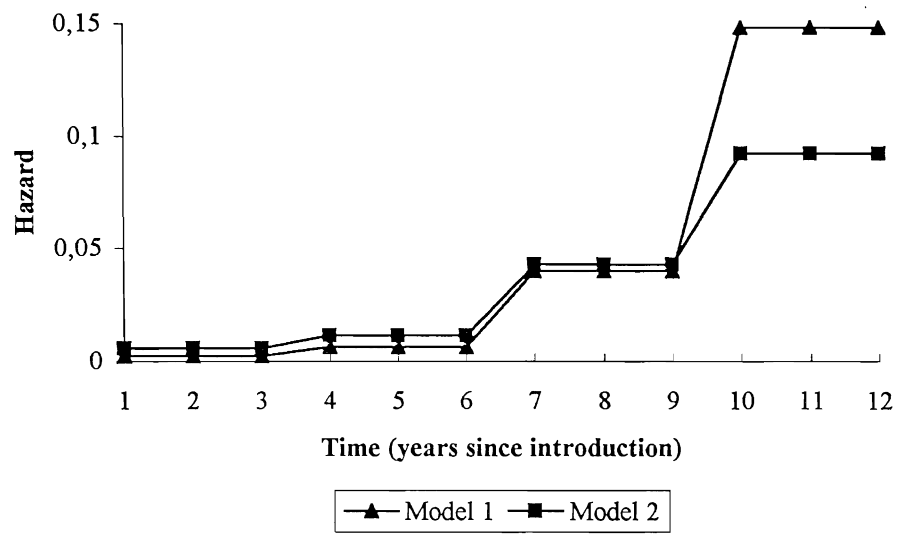



**Figure 3. Evolution of the Hazard Rate**




Note: The "average" non-communist country considered has a GNP per Capita of 5,065, a crude death rate of 9.4, 5 ethnic groups and 8 major population centers.
Model 1: with correction for unobserved heterogeneity
Model 2: without correction for unobserved heterogeneity