DEPARTEMENT TOEGEPASTE ECONOMISCHE WETENSCHAPPEN

ONDERZOEKSRAPPORT NR 9502

Modelling Global Diffusion

by

Marnik G. DEKIMPE

Philip M. PARKER

Miklos SARVARY

Katholieke Universiteit Leuven

Naamsestraat 69, B - 3000 Leuven

ONDERZOEKSRAPPORT NR 9502

Modelling Global Diffusion

by

Marnik G. DEKIMPE

Philip M. PARKER

Miklos SARVARY

D/1995/2376/2

Modelling Global Diffusion

Marnik G. Dekimpe
Philip M. Parker
Miklos Sarvary

January 1995

Marnik G. Dekimpe is Assistant Professor, Catholic University Leuven, Naamsestraat 69, 3000 Leuven, Belgium (Tel. 32-16-326 944; E-mail: marnik.dekimpe@econ.kuleuven.ac.be); Philip M. Parker is Associate Professor, INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France (Tel. 33-1-6072 4000; E-mail: parker@insead.fr); Miklos Sarvary is Doctoral Candidate, INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France (Tel. 33-1-6072 4000; E-mail: sarvary@insead.fr). The authors are listed alphabetically.

We would like to thank Marie-Louise Berry, William Fisk, Katrijn Gielens, Eva Szekeres and Hagit Zeev for their excellent research support, and Hubert Gatignon, Dominique Hanssens, Donald Morrison, Sunil Sharma, Piet Vanden Abeele and Linda Van de Gucht for useful comments on an earlier draft of the paper. We are also indebted to Andrew Roscoe and Jonathan Tarlin of EMCI, Inc. and Claes Tadne of Ericsson Radio Systems who supplied industry insight for this research.

Modelling Global Diffusion

Abstract

This paper presents a general model of global diffusion processes. The approach recognizes "breadth" and "depth" of adoption by first considering the sequential introduction of the innovation across countries (breadth). Given the time of introduction into a specific country, within-country diffusion (depth) is subsequently modelled. We illustrate the approach using data from the cellular telephone industry for 184 countries. The proposed approach provides empirical insights which could not have been obtained using traditional techniques. In particular, we show that breadth and depth processes are not necessarily affected by the same socioeconomic factors. We also are able to evaluate the importance of the *linkage* between the two processes.

"When it comes to product strategy, managing in a borderless world doesn't mean managing by averages." (*The Borderless World*, Kenichi Ohmae, McKinsey & Company, 1990, p. 24).

1. INTRODUCTION

The marketing of globalized products produces a number of challenges to firms hoping to serve international markets. Believing that there is an "average" country or assuming that the home market's behavior will be replicated elsewhere may ignore important variances likely to be faced by products going global. In this paper, we propose a formal approach designed to investigate and explain variances in globalization patterns. In particular, we are interested in understanding forces which affect the global acceptance of a given product or service, and provide a vehicle to test theories as to why this acceptance may vary from one country to another. In doing so, we hope to extend the literature on innovation diffusion (e.g. Robertson 1967, 1971; Rogers 1983) to the study of product acceptance across the entire community of nations. Since the 1960s, several new-product diffusion models have been developed and documented in the marketing literature which are specifically designed to evaluate new-product acceptance over time, and a number of reviews have considered in great detail their descriptive, predictive and normative use (e.g. Bridges, Coughlan and Kalish 1991; Hanssens, Parsons and Schultz 1990; Lilien, Kotler and Moorthy 1992; Mahajan, Muller and Bass 1990; Simon 1989). These reviews reveal that existing models are well suited to one-country, one-product situations. Most products are launched or sold, however, in multiple countries or geographic regions, and undergo global diffusion processes. Recently, a number of comparative studies have started to consider differences in diffusion patterns across countries. Our study contributes to this stream of work in a number of ways.

First, previous research on international diffusion has mainly dealt with comparisons of diffusion rates across a limited set of industrialized countries (see Table 1). As a consequence, over 90 percent of the world's nations are ignored, and key countries like Brazil, Indonesia, China, India and Russia which together represent over 40 percent of the world's population are mostly excluded.[1] This tendency to focus on only a few countries is mirrored in a broader survey of the international marketing literature. Table 2 shows that of 111 international marketing studies published since 1975 in 25 major marketing and management journals, only one reported a sample exceeding 50 countries. In this paper, we investigate global adoption and diffusion by considering 184 countries located in Africa (55 countries), Asia (37 countries), Europe (32 countries), the Americas (45 countries) and other regions (15, mostly island, countries).[2]

Insert Tables 1 and 2 about here

Second, beyond considering the entire community of nations, we identify and model two distinct components of the global diffusion process. Consider, for example, 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, the global adoption curve inherently masks two underlying and fundamentally different processes:

- adoption timing across countries; i.e. when will each individual country first show, or allow, the sales of the innovation, and
- within-country diffusion process; i.e. given the adoption time, what are the likely diffusion rates within a given country?

We label these processes *breadth* and *depth* of adoption, respectively. From the manager's point of view, a comprehensive understanding of these two distinct dimensions is required. Knowing when a country will first adopt a product does not indicate, by itself, that it warrants certain marketing activities (e.g. the market potential may be too small). Likewise, knowing that a country will have a large market potential and fast penetration rate may be

---

[1] Some of these countries were considered by Heeler and Hustad (1980) in their study on the diffusion of black and white TV and refrigerators. Still, the number of countries they considered was less than twenty.

[2]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).

inconsequential to planning if the country will only begin adoption well beyond the planning horizon. From an academic perspective, breadth and depth processes result in two distinct modelling approaches. The data investigated are disaggregate in the former case (i.e. each country is an individual adopter), but are aggregated in the latter (i.e. the penetration rates within each country). By modelling both breadth and depth, we can determine if factors hypothesized to affect global diffusion have similar or differing influences on the different components of the process. Moreover, by considering both dimensions, we are able to investigate possible *linkages* between the two, e.g. does the adoption timing affect the subsequent rate of diffusion within a country? With respect to prior diffusion research, Table 1 shows that only the second aspect (depth) has received attention in the literature, while the former (breadth) has been completely overlooked. Likewise, no study has thoroughly considered the linkages between the two.

Insert Figure 1 about here

Third, diffusion theory suggests that differences in the diffusion pattern of a technology across countries may be due to both exogenous and endogenous factors, but empirical studies have mainly considered the impact of the former. Gatignon et al. (1989), for example, assessed the impact of a country's degree of cosmopolitanism, mobility and sex roles (all factors exogenous to the diffusion process) on its propensity to innovate and imitate, but did not model the impact of endogenous factors (e.g. number of countries which have already adopted). Some (indirect) evidence of endogenous influence is found in Takada and Jain (1991), who found the diffusion process to be a function of the country's adoption timing; the number and nature (similarity) of previously adopting countries was not considered, however. Our approach estimates cross-country heterogeneity in both breadth and depth processes while simultaneously incorporating exogenous and diffusion-driven (endogenous) covariates. As such, a more complete picture of the relative importance of exogenous versus endogenous forces is obtained.

Fourth, from a methodological point of view, the proposed modelling approaches have a number of advantages over existing techniques. With respect to the adoption timing across countries (breadth), a flexible hazard specification is proposed which explicitly takes the grouped nature of the data into account, allows for a non-parametric specification of the time dependence, includes both fixed and time-varying covariates, accounts for unobserved heterogeneity and does not require all countries to ultimately adopt. While each of these individual features has been applied before in the marketing 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, which, in our context, is needed to ensure consistency of the parameter estimates. In terms of the within-country diffusion (depth), the international nature of the process elucidated a number of problems with earlier specifications. To this end we improve upon existing aggregate diffusion models in three respects: (1) we are the first to apply "sample matching" which is required in cross-cultural research but overlooked in the diffusion literature, (2) we make explicit the need for a comparable "time of origin" and thereby overcome problems caused by left-hand adoption-curve truncation, and (3) we propose a staged estimation procedure which results in more plausible parameter estimates than extant techniques.[3] Combined, these three extensions considerably attenuate Simon's (1994, p. 14) criticism that aggregate diffusion models are "risky and potentially misleading", and show that this conclusion may be more a function of the estimation procedures used than of the intrinsic quality of the diffusion models themselves.

Finally, the paper tests a variety of international theories suggested in the diffusion literature (e.g. Gatignon and Robertson 1985; Rogers 1983). Our study provides substantive insights, for example, into the effects of various country traits on the diffusion process, including ethnic homogeneity, economic development, political disposition, levels of competition and cross-country influence. We must qualify our contribution, however, since we use only one industry to illustrate the modelling approach. We do not, therefore, claim that the results are generalizable to every other product category; still, they represent a first attempt at testing prevailing theories.

We illustrate our approach using diffusion data from the cellular telephone industry.

---

[3]Each of these properties is discussed in Section 4, where we also compare our approach with existing specifications.

In Section 2, we provide some background information on the nature of this diffusion process, and mention a number of pragmatic concerns associated with empirical studies of global marketing phenomena. Next, we report and apply the modelling approaches for the breadth (Section 3) and depth (Section 4) dimensions of the diffusion process. In Section 5 we conclude with a discussion on some of the implementation issues involved, and present areas for future research.

2. DATA ISSUES

2.1. The Nature of the Considered Diffusion Process

While we use the cellular-telephone industry as an illustration, we want to emphasize up front that the modelling concepts presented in Sections 3 and 4 are applicable to any situation where managers or researchers have some indication of the domestic or foreign-market demand for the new product, and are interested in likely demand dynamics across countries. Assuming that an innovation is launched in the "home" market (e.g. Japan as was the case for cellular-telephone services in 1979), cross-country diffusion takes place when adoption begins in other countries. This may be the result of what Rogers (1983) calls a *centralized* process whereby the firm (i.e. the change agent) systematically determines where the innovation should be sold next. In other instances, diffusion may be of a *decentralized* nature. For durable products, for example, international diffusion may begin as unsolicited exports, with independent channel members selling in foreign markets without the manufacturer's knowledge or explicit action. In this paper, we mostly consider decentralized processes where the manufacturers themselves do not determine when sales will begin in a specific country, but where foreign governments determine (even though the firms may try to influence that decision) from what point in time the product or service is allowed to be sold in their country. Such processes are likely to exist for a wide variety of product categories such as most medical 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. When firms themselves plan the introduction sequence (i.e. when dealing with centralized processes), one can still use the proposed modelling techniques as research tools, though the nature of the explanatory variables may be somewhat different.

2.2. 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 theory can be 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 innovations 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 product categories (e.g. nuclear submarines). As such, we do not claim that the covariates included in our study should be equally relevant for all other product categories. 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, and also the development of multi-item scales was infeasible.[4]

Given these concerns (that theories/hypotheses are likely to be category specific, and

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

that proxies are required, but limited in number), the hypotheses tested here represent the intersection of three considerations: (1) support in the diffusion literature, (2) managerial relevance, and (3) data availability. Specifically, we assess the impact of exogenous forces including political disposition (communist or not), socioeconomic characteristics (GNP per capita, crude death rate, population growth), competition (number of competitors), social-system homogeneity (number of ethnic groups) and population concentration (number of major population centers). We also consider the role of endogenous factors including the importance of the demonstration effect exerted by earlier adoptions in "similar" countries.

3. STUDY #1: THE BREADTH DIMENSION OF GLOBAL DIFFUSION

3.1. Introduction

Table 3 classifies countries having introduced cellular services using the "innovator-laggard" spectrum proposed by Rogers (1983),[5] whereby late-majority and laggard countries are those which had yet to offer the service in 1993. The great variability in adoption times is also reflected in Figure 2 which shows both the actual number of countries introducing the service in a given year and the number of adopters predicted by the aggregate diffusion model of Easingwood, Mahajan and Muller (1983). Even though the latter approach gives a parsimonious description of how fast the innovation 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.

Insert Table 3 and Figure 2 about here

Micro-level models relax this homogeneity assumption, and allow the probability of adoption to be heterogenous across potential adopters (Chatterjee and Eliashberg 1990; Sinha and

[5]A similar classification can be made using the methodology proposed by Mahajan, Muller, and Srivastava (1990).

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. In our first study, we extend these approaches to international diffusion processes where our units of observation are countries rather than firms.

3.2. Model Development

To explain the variance in international adoption timing, a flexible hazard model is used 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 innovation.

Let T denote the random duration until a country adopts the innovation 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.[6] For those countries which had not yet adopted a cellular system by

[6]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.

September 1990 (the right-censored observations), a duration of 12 years is recorded.[7]

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 $S(t_k\text{-}1)$-$S(t_k)$, 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).[8] 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 conditional probability

[7]In study #1, 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 beyond September 1990 would also have affected the sample size in that the national boundaries of a number of countries have changed.

[8]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).

that country i will adopt in duration interval t given that it has not done so by the end of interval t-1, 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, λ_0 gives the adoption probability of countries in the base group in the first year after the technology's introduction. The base group is defined as 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 β 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.[9] 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 λ_0, no dummy variable is included for the first year. As such, λ_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. 1994). 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 1986, 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

---

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

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.[10]

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. 1994):

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

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

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

In Equation (5), we basically assume that every country in the base group has the same initial adoption probability λ_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 innovations), 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 λ_0 be distributed

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

according to a gamma mixing distribution.[11] This mixing distribution is quite flexible, and has been shown to result in the following closed-form solution for the likelihood function (see Vanhuele et al. 1994 for a formal proof):

$$LL = \sum_{i=1}^{N} \ln\{(1+d_i)\,[\frac{a}{B_i(t_i-1)+a}]^r - [\frac{a}{B_i(t_i-1)+(1-d_i)\,e^{\beta X_i(t_i)+cD_i(t_i)}+a}]^r\}. \quad (6)$$

The average first-year adoption probability 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 a vis λ_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). Mathematical derivations are presented in Appendix A, but intuitively, this approach allows for a discrete spike at $\lambda_0 = 0$. The magnitude of this spike allows us to test the managerial intuition that in the long run all countries will adopt the innovation. The model in Equation (A.2) 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 marketing applications of hazard-rate models is given in Table 4. This table illustrates that our model is the first to integrate all aforementioned properties.

---

[11]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).

Insert Table 4 about here

3.3. Empirical Findings

The models described in Section 3.2. are used to test the impact of a number of exogenous and endogenous factors on the timing of a country's decision to adopt cellular telephones. Data on the cellular telephone industry were collected from the relevant government agencies, trade associations, and the International Telecommunications Union, a United Nations Agency.[12] The exogenous covariates reflect political (communist or not), demographic (average annual population growth, number of major population centers), economic (GNP per Capita, crude death rate) and social-system (number of ethnic groups) characteristics. These data were collected from Euromonitor Ltd. and the *World Factbook* (Central Intelligence Agency, 1993). Relevant summary statistics are presented in Table 5.[13] The highest correlation between the respective variables does not exceed 0.4, suggesting that multicollinearity is not a problem.

Insert Table 5 about here

In addition to these exogenous forces, we also consider the endogenous effect suggested by Gatignon and Robertson (1985, p. 858) 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

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

[13] 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.

end of the previous grouping interval.[14] 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).

Parameter estimates for a number of different model specifications are given in Table 6. In Table 6, we still impose the managerial assumption that all countries will eventually adopt; we will test that assumption later on.

Insert Table 6 about here

The first column of Table 6 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 product category. 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 (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

[14]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.

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 conditional adoption probability for an "average" non-communist country.

Insert Figure 3 about here

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 6), and found the results to be very similar across the two samples. The main difference appears in the initial base hazard (*r/a*) 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 conditional probability of adoption 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 δ in Appendix A) 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.

3.4. Summary

In this first study, we 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 innovations, 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. STUDY #2: THE DEPTH DIMENSION OF GLOBAL DIFFUSION

4.1. Introduction

Having explained the *cross-country* variance in adoption times in Section 3, we subsequently assess the influence of exogenous and endogenous forces on two basic components of the *within-country* adoption patterns: (1) the first-year penetration level (the intercept of the penetration curve), and (2) the speed of adoption between initial penetration and long-run ceiling. Another point of interest is the possible *linkage* between the timing of adoption and the subsequent adoption depth.

Simon recently concluded that aggregate diffusion models "are risky and potentially misleading" (1994, p. 34). This observation appears especially true within international contexts. Schmittlein and Mahajan (1982) suggest that diffusion models typically require 10 or more observations to be estimable (or the data must cover periods beyond the penetration curve's inflection point), which may be difficult to attain in international studies (Heeler and Hustad 1980). Even though their data series had 15 degrees of freedom each, Gatignon et al. (1989) report that almost 30 percent of their models yielded implausible estimates. In our application to the cellular telephone industry, only 57 countries had sufficient degrees of freedom (i.e. at least 3 data points) to estimate traditional diffusion models. Table 7 reports the parameter estimates resulting from a "blind application" of the original Bass (1969) model using nonlinear least squares estimation (see Srinivasan and Mason 1986). In almost 95 percent of the cases,[15] implausible results (wrong signs or insignificant results) were obtained, which obviously would prevent subsequent analyses to explain variances across countries.

---

[15] Exceptions are Denmark, The Netherlands, Norway and the United States.

Insert Table 7 about here

Despite this apparent evidence in support of Simon's statement, we will demonstrate that his conclusion may be more a function of the context and estimation procedures used than of the intrinsic quality of the models. We present a "staged estimation procedure" which (1) results in plausible estimates, (2) provides sufficient flexibility to model cross-country heterogeneity via exogenous/endogenous covariates, and (3) provides a reasonable basis upon which hypotheses can be tested when only the earliest adoption figures are available (e.g. after only one year of diffusion or several years prior to the inflection point).

4.2. Model Development

To make a valid comparison of diffusion patterns across countries, one has to correct for the fact that their introduction timing may vary widely. In the cellular industry, for example, Japan adopted in 1979 while the United States postponed their adoption decision until 1983 (see also Table 3). If one ignores that country-level diffusion patterns have different origins in time, time-specific cross-sectional measures will reflect a different temporal stage of each country's penetration curve (see Figure 4 for a graphical illustration).

Insert Figure 4 about here

In addition to precluding an assessment of the impact of the introduction timing (delay) on subsequent penetration growth, a failure to recognize differences in introduction date can also lead to left-hand truncation bias.[16] By assuming a fixed temporal window (e.g. 1966-1980 for all countries when one country started adoption in 1959 and another in 1965), diffusion curves are truncated to the left with only some countries having their initial year included. This truncation or shift in the time origin inflates the intercept value of the penetration curve, and therefore, the estimate of external influence. As shown in Table 1, several international

[16]Obviously, this problem is largely driven by data availability, or lags between product introduction and data reporting.

diffusion studies have been affected by left-hand truncation bias.

To overcome these problems, we use the first year of within-country penetration (i.e. after 12 months) as a time origin which is comparable across countries.[17] Time t therefore measures the number of years elapsed since the country has adopted the innovation ($t \geq 1$). For a given country, i, we define the following time-series adoption function based on the three-parameter Bass model:[18]

$$n_{i,t} = [a_i + b_i (\frac{N_{i,t-1}}{c_i S_i})] [c_i S_i - N_{i,t-1}] , t = \{1, 2, ...\} , \tag{7}$$

where a_i, b_i and c_i are constants, $n_{i,t}$ is the number of adoptions in time period t, and $N_{i,t-1}$ is the number of cumulative adoptions up to t-1. By definition, t is equal to 1 at the origin, and $N_{i,0}$ equals zero. S_i measures the social-system size (e.g. the population or the number of households) and c_i is the long-run adoption ceiling ($0 \leq c_i \leq 1$). The term $c_i S_i$ therefore measures the long-run adoption potential, and is analogous to the "market potential" in the original Bass model. In the diffusion literature, a_i is typically interpreted as the external influence (or innovation) coefficient. In our model, this parameter can also be interpreted, in an agnostic manner, as the penetration curve intercept. Since the origin is put at t=1 (as opposed to t=0), and since $n_{i,1}$ measures the number of first-year adopters, a_i is given by $[n_{i,1} / c_i S_i]$.[19] The first year penetration level is therefore an *exact* estimate of this parameter (provided that the potential is defined). Finally, b_i reflects the growth rate between the intercept and the potential, and is often called the coefficient of internal or imitative influences (Mahajan, Muller and Bass 1990).

To explain cross-country variances in the diffusion patterns, we incorporate country-specific covariates in the diffusion parameters. To ensure that a_i and b_i lie between zero and one, the following logistic transformations are used:

---

[17]This origin could be the first month or week if the data were collected at these time intervals.

[18]See Kamakura and Balasubramanian (1988), Parker (1992) or Schmittlein and Mahajan (1982) for similar formulations.

[19] If c_i or S_i are dynamic in time, the value of the first-year penetration is computed with respect to the social-system size in the first year (t=1).

$$a_i = [1 + e^{-d_1 X_i}]^{-1} \tag{8}$$

$$b_i = [1 + e^{-d_2 X_i}]^{-1}, \tag{9}$$

where X is a set of exogenous (e.g. GNP/Capita) and/or endogenous (e.g. proportion of previous adopters) covariates, and where d_1 and d_2 are sets of parameters.[20]

Pooling (i.e. stacking) the base-line model across countries, the following "global" or "generalized" depth diffusion model is obtained:

$$n_t = [A + B * (\frac{N_{t-1}}{C * S})] [C * S - N_{t-1}] \tag{10}$$

where A, B and C are cross-sectional vector variables; n_t and N_t are vectors obtained by stacking $n_{i,t}$ and $N_{i,t}$ respectively, and vary over time across countries; S is the social system-size vector. In Equation (10), "+", "*" and "-" refer to element-wise operations. Hence, for example, the j-th element of $C*S$ is given by $c_j S_j$, and the j-th element of $[B * (N_{t-1} / C*S)]$ is given by $[b_j N_{j,t-1}/(c_j S_j)]$. This model is similar in spirit to that proposed in Gatignon et al. (1989), with the exception of the inclusion of the ceiling (C) and social-system-size (S) vectors, the recognition of a comparable time origin of innovation age (t=1), and the incorporation of covariates via the logistic transformation.[21]

[20]The linear form $d_l X_i$ (l=1, 2) is used for simplicity. However, one can easily generalize (8) and (9) to more complex relationships $f_l(X_i)$.

[21]The reader will note that we do not include independent cross-country influences beyond the intercept, a_i, and growth parameter, b_i. Including independent effects (e.g. the isolated effect of Panama on Singapore) proves problematic for three reasons: (1) it generates severe multicollinearity, (2) it does not allow for the separation of cross-country effects on the initial penetration level, a_i, or the long-run growth rate, b_i, and (3) it is unimplementable when the diffusion rates are separately included for all countries of the world.

4.3 Staged Estimation

We propose a staged estimation procedure for this general model which is logically consistent with diffusion paradigms. The approach consists of three stages which, we argue, should occur in the following sequence: (1) *external* estimation of the social-system sizes and long-run adoption ceilings, c_iS_i across countries, (2) calculation or *external* estimation of the intercept term, a_i, and (3) *internal* estimation of the growth parameter, b_i, for each country. The temporal order of the three stages reflects the evolutionary nature of a diffusion process which proceeds based on a strict hierarchy of necessary conditions: initial adoption depends on the prior existence of a social system, and growth processes are always preceded by an initial introduction or acceptance level. As described below, each stage relies on a unique procedure which supplies manifestly superior estimates to traditional approaches. The staged methodology also takes advantage of certain characteristics of Equations (7) and (10) and fully uses each observation, regardless of the temporal length or cross-sectional nature of the data available. As such, it is especially useful to managers or researchers interested in understanding cross-country variances at the early stages of the international life cycle.

4.3.1. Stage #1: The Social System and Sample Matching

A number of authors recommend estimating long-run adoption potentials externally to diffusion models (e.g. Heeler and Hustad 1980; Srinivasan and Mason 1986; Tigert and Farivar 1981). Two considerations support this approach: (1) as mentioned before, there may be insufficient degrees of freedom to internally estimate the potential, and (2) both c_i and S_i may be fundamentally driven by processes which are product independent (e.g. population growth rates). The first, more practical, concern often arises in international diffusion studies, especially during the early years of the international product life cycle. The second, more theoretical, reason requires that international diffusion studies match social-system parameters on clearly-defined, yet externally-established criteria, a procedure called "sample matching" in cross-cultural research (Dawar and Parker 1994). Sample matching essentially forces the researcher to make comparisons within comparable social networks to make valid statements on cross-cultural effects. This is consistent with diffusion theory which suggests that diffusion processes are limited to social networks which will ultimately perceive the innovation, among other criteria, as being compatible with social norms or to be a relative advantage to existing substitutes (Rogers 1983). Specifically, to compare the diffusion of medical equipment across countries, one may externally limit the discussion to hospitals. Similarly, farmers may be a more relevant social network to study the diffusion of farm equipment than the entire population.

Using the cellular-telephone industry as an example, Figure 5 illustrates the importance of sample matching in cross-cultural diffusion research. The top graph displays temporal penetration patterns across a sample of countries. In order to plot the data in terms of penetration (as opposed to subscriptions), we are required to externally impose a definition of the relevant market. A popular measure in the industry is to define the market as the total population in the country (c_i=1 for all countries, and S_i is the population), and to express penetration as "penetration per pop". From the top figure, we might conclude that Scandinavian countries have a greater proneness to innovate, or exhibit high levels of word-of-mouth influence (say, due to their citizens being highly mobile and cosmopolitan). The bottom graph in Figure 5 illustrates penetration levels when the ceiling parameter is matched across countries on the following criteria: "the percentage of the population who is literate, lives in urban areas and has a sufficient income to afford basic telephone service".[22] This definition of potential can be judged theoretically superior to the total population (the industry norm) because it better reflects the actual network within which the diffusion process occurs. If we accept this second definition of potential, the bottom graph in Figure 5 is obtained. When contrasting the top and bottom graphs, we clearly see that "innovative" behavior under one definition of potential appears less so under another, and high-growth markets are transformed into slow-growth markets when the definition of market potential is matched across cultures. Innovative countries are no longer Scandinavian, but South-East Asian.

[22]Data on these percentages are obtained from the sources given in Section 3.3.

Insert Figure 5 about here

Unless market potentials (social systems) are matched on theoretical or managerial grounds, comparisons of diffusion-growth parameters may be arbitrary or, worse, misleading. In sum, we strongly argue that **the market potential definition must precede any discussion of theories affecting growth** (e.g. innovative or interpersonal influences).[23] This argument rejects blind "curve fitting" (as in Table 7) in favor of explaining innovation adoption growth within theoretically identified social networks.[24]

4.3.2 Stage #2: The Penetration Curve Intercept

The second stage involves estimating the first-year intercept, a_i (the external-influence parameter), which by definition precedes in time any growth process or internal influence. Two cases can be distinguished: (1) when countries have some experience, and (2) when countries have no experience. In the first case, we propose that the modeler takes advantage of the "intercept property" of a_i in Equation (7), and fix a_i as the first-year penetration level: $a_i = n_{i,1}/(c_iS_i)$. This property exists as long as the data are consistently analyzed with an identical origin and over the same discrete time interval for all countries (e.g. daily, weekly, monthly, annually). Clearly, a_i depends on c_iS_i being pre-defined. Put differently, to speak of "penetration" in the first year, one needs to clarify (externally impose) "of what". This agnostic interpretation of a_i generates the most efficient use of the theoretical (as opposed to statistical) degree of freedom offered by the first data point in the series. The reader will note that the second, or any subsequent, data point in the series provides no information on this parameter's

---

[23]This conclusion is "fit-statistic" independent as we can develop models which fit curves from both figures equally well.

[24]We want to point out that external growth mechanisms may make it necessary to use dynamic ceiling and/or system-size estimates (e.g. population growth for S_i, or economic development for c_i). Data for these estimates may come from a variety of public agencies or private vendors (the World Bank, the United Nations, the International Monetary Fund, Euromonitor). In cases of extreme doubt (diffuse priors), c_i can be set equal to 1.0 for all countries, in which case the matching would only occur in terms of S_i.

estimate as the intercept is already known and fixed by time period 2. Hence, **a_i should not be internally estimated using time series data**. Internal estimation of a_i needlessly increases the instability of this parameter.

For each country where one does not have the first data point, one can derive an estimate (forecast) of a_i using the logistic function in (8). This estimation is based on data from the adopting countries, and is conducted externally to the pooled model using nonlinear least squares. The explanatory performance of this model clearly increases as more countries experience their first-year adoption level, since both the statistical degrees of freedom and the variance in the covariates will increase. Once an external estimate is made for a_i, it is fixed at this value for the next stage. When the actual intercept value becomes available for a given country, this data point updates (replaces) the estimate of a_i, and we no longer make use of the cross-sectional model to estimate this parameter for that particular country.

4.3.3 Stage #3: Penetration Growth

The third stage in the sequence requires an estimate of the growth rate. As before, two cases are relevant: (1) when data are unavailable for a given country (i.e. when there is no more than one observation of experience), and (2) when data are available past the first observation. In the first case we generate estimates of b_i by imposing A, C, and S on the pooled model and incorporating covariates nested in the logistic transformation given in Equation (9). In the second case, as within-country degrees of freedom increase, an individual country's b_i can, as suggested by Gatignon et al. (1989), be estimated exclusively using that country's data.[25] The parameters c_i, S_i and a_i remain, of course, fixed in order to estimate b_i, even though the series may have several observations.

---

[25]Within the cellular industry, our analyses indicated that with one or more degrees of freedom beyond the intercept observation (which is always used to calculate a_i), 63 percent of the estimates of b_i were both plausible and significant; after 4 observations, over 80 percent, and after 7 or more observations beyond the intercept, over 95 percent of the estimates were both plausible and significant.

4.4. Empirical Application to the Cellular Industry

4.4.1 Stage #1: The Long-Run Potential (c_iS_i)

Definitions

A number of social system definitions and ceilings were considered which could be matched across cultures. For this application, the social system, S_i, is defined as each country's population. Based on industry interviews, the ceiling parameter, c_i, is defined as described earlier: "the percentage of the literate population living in urban areas having a sufficient income to afford basic telephone service". This definition of the long-run ceiling, c_i, reflects the "AT&T vision" of mobile communications.[26] Cellular services, as externally judged by several managers in the industry, will remain an urban (village, town or city) oriented service which could potentially (in the long run) replace or be a direct complement to fixed or conventional service; rural areas are expected to be serviced by digital wireless technologies (Basic Exchange Radio Telephone Services - BETRs) or conventional services in the long run.

This ceiling foresees over the next decade "flat phones" (i.e. with credit card or smaller size/weight) which will have battery lives and prices comparable to electric watches. A going assumption is that the barrier to adoption will not be the handset price. This assumption foresees that these and other terminal models will ultimately (in the long run) be one-to-one complements to all urban wire-based telephones and in many countries, especially former communist and developing countries, direct substitutes to wire-based systems which are too costly to implement. This external estimate of the ceiling has the advantage of further limiting the social system to a *relevant* population; the target market being limited to literate persons with a minimum purchasing power is a de-facto limitation on age (i.e. excludes infants).[27]

Appendix B reports c_i and S_i for the 184 countries studied. For the sake of illustration,

---

[26]We would like thank Claes Tadne of Ericsson Radio Systems for this insight.

[27]Alternative definitions of social system (e.g. based on the number of automobiles, all moving vehicles, households, etc.), were considered but not reported here as they either generated similar results, were less theoretically appealing, or were rejected due to a lack of data availability.

and since the time period studied is limited in duration, we assume c_i and S_i to be time-invariant. The social-system size ranges from 2,000 persons in the Falkland Islands, to over 1.1 billion in China; the average country size is approximately 29 million, or the size of Morocco. The ceiling parameter, c_i, ranges from less than 1 percent, in Rwanda, to 99 percent, in Monaco; an average country is Portugal at 17 percent. The long-run potential ($c_i S_i$) ranges from 100 subscriptions in Tuvalu, to over 180 million, in the United States; a country of average potential is Turkey with 3 million subscribers. Should we wish to apply the models within a long-run, or multiple-decade. forecasting exercise (as opposed to testing prevailing theories over the historical range of the data), we would forecast changes in c_i and S_i using external models which would foresee changes in urbanization, literacy and income levels. This would be especially important for countries like China whose c_i parameter is estimated to be less than 1 percent (though the total subscriber potential still exceeds 5 million).

Validation

An external imposition of the adoption ceiling does not guarantee that it will, in some way, reflect theories of diffusion. Yet, in unreported tests, the adopted ceiling parameter was found to be significantly correlated with theoretically motivated covariates. For example, it varies significantly with the income per capita in each country, which supports Gatignon and Robertson's (1985, p. 858) suggestion that long-run penetration is a function of the innovation's compatibility and normative fit within the social system. In contrast, the industry norm in defining the potential (penetration per "pop") generally fails to correlate with these theoretically appealing covariates. We will now test the face validity of our estimates of c_i and S_i using naive pooled models.

Table 8 summarizes *naive* applications of the pooled model in order to compare internal versus external estimation of the social system and ceiling parameters. Model 1 can be considered the base-case model in that it internally estimates all parameters which are assumed constant across countries: the average or typical diffusion curve. The model, in addition to having a statistically insignificant intercept, indicates an average potential of 18.7 million subscribers. The high reported fit statistic (R^2_a=0.93) is deceptive in suggesting that this fixed-parameter model provides meaningful or highly explanatory results. In fact, if we accept that the level of subscriptions will not exceed, in the long-run, every man, woman and child on the planet, then the "average" potential (18,679 thousand subscriptions) is implausible for over 134 countries of the world whose population does not exceed 18 million persons. This result strongly supports the argument for external controls for country heterogeneity. Model 2 partially fulfills this role by imposing a social-system size, S, but it internally estimates the "average" ceiling, intercept, and growth parameter. We see that the model is worse on average, and that it yields implausible coefficients: a significantly negative intercept and a negligible growth rate. The ceiling estimate of 6 percent appears plausible at first, yet it is completely inappropriate for 101 countries which have less than 6 percent of their populations living in urban areas, or having the financial means to own basic telephone service (see Appendix B). This result shows that it is insufficient to control for social-system sizes alone and let the model indicate a ceiling level. Imposing a "diffuse-prior" estimate of c_i=1.0 for all countries (see Footnote 24), Model 3 yields plausible and significant results for both intercept and growth parameters. As shown in Model 4, the imposition of the aforementioned managerial priors (reflected in the vector variable C), provides some improvement: significant and plausible parameter estimates are obtained, and the fit statistics are superior. A comparison of these four models lends some face validity to our argument that a staged estimation procedure should be followed where social-system sizes and ceiling parameters are estimated externally prior to estimating other diffusion parameters. Even so, Model 4 provides a single intercept estimate of 0.17 percent which is an inappropriate estimate for most countries studied. We are therefore left to explain heterogeneity in initial adoption levels (A) and growth rates (B) across countries.

Insert Table 8 about here

4.4.2. Stages 2 and 3: Intercept and Growth Parameters (a_i, b_i)

Given matched definitions of the potential across social systems, we can *calculate* the first year penetration percent which is used as an *exact* estimate of the intercept parameter, a_i, for those countries which have at least one year's experience; these estimates are available for 74 countries and are reported in Appendix B with an "*" sign.[28] Values range from a high of 3.3 percent (in Brunei) to a low of .0007 percent in Spain. As we are interested in explaining variations across countries and to provide estimates of first-year adoption in countries having no experience, we apply the logistic model in Equation (8) and incorporate the explanatory covariates given in Table 5. Likewise, having now obtained vector variables of intercept values, A, ceiling levels, C, and system sizes, S, we can in Stage #3 estimate the pooled model (10).

Table 9 summarizes estimations of Equations (8) and (10). Besides the exogenous covariates we include endogenous covariates (number of other countries having adopted, and the proportion of World Bank countries having adopted) to investigate the linkage between a country's adoption timing (Study #1) and its penetration curve. Table 9 reports the full model with all covariates included as well as a retained model which proved the most parsimonious with all covariates remaining significant (multicollinearity effects across covariates are negligible). Likelihood-ratio tests reveal statistical equivalence between the retained and full models (chi-square test *p-value*>.20). This comparison indicates stability in the covariate's parameter estimates. The models support the notion that poverty (crude death rates), which acts a cross-country surrogate for real relative prices (i.e. the price of cellular will always appear higher to impoverished populations), and ethnic heterogeneity decrease initial adoption levels. Our result for the ethnic-heterogeneity variable support Gatignon and Robertson's (1985, p. 858) contention that "the more homogenous the social system, the faster the diffusion rate". Initial penetration seems to also decrease with the number of major population centers.

---

[28] The reader will note that we have more adopting countries than in Study #1 which limited the sample to the de-facto date of German reunification (to avoid ambiguities in defining countries); here this constraint need not be imposed.

Intuitively, the more centers to be covered by the network, the more difficult to provide ubiquitous coverage in the first year. Influences which are positively related to initial penetration levels include population growth rates (a surrogate for the need to expand telecommunications infrastructure) and the number of competing systems; this second relationship is again supported in the diffusion literature as Gatignon and Robertson (p. 861) suggest that "the greater the level of competitive activity, the faster the rate of diffusion". All other influences are marginal or are statistically insignificant (e.g. GNP per capita, and communism). With respect to the linkage between innovation timing (Study #1) and initial penetration levels, no endogenous covariate proved explanatory for the first year penetration level. These or alternative endogenous covariates (year of adoption, or total number of world-wide subscribers) whether incorporated simultaneously or one-at-a-time were consistently found to be unrelated to first year penetration levels.

Insert Table 9 about here

In terms of the diffusion growth rates (b_i), crude death rates and the number of ethnic groups all have negative influence on diffusion rates, whereas only the number of major population centers has a positive effect (i.e. the higher the number of centers, the lower the initial penetration level, yet the faster the growth to the ceiling). Population growth, state-control over the economy, and GNP per capita have no influence on growth rates. Mahajan, Muller and Bass (1990, p. 21) ask: "How does the number of [competitors] available in the market affect the growth of a product?" In the case of cellular services, no relationship is found between the number of competitors and the diffusion growth rate. As was the case for initial penetration, adoption timing or any other endogenous covariate has no influence on b_i.

Using the retained models given in Table 9, Appendix B reports the calculated estimates for a_i and b_i for all countries, including those which have yet to adopt cellular technology. In addition to generating high fit statistics, the reader will note that all values are plausible and, hence, manifestly superior to those obtained using traditional estimation procedures (see Table 7). We see that the variances in global diffusion patterns are explained by variances in social system characteristics which affect long run ceilings (which vary between .001 and .99) and social system sizes (which vary between 2,000 and 1.1 billion), variances in the initial penetration level (which varies between .00001 and .033, based on Equation 8), and variances in the growth rate coefficient (from .001 to .705, based on Equation 9). Such low estimates for both diffusion parameters are infrequently seen in the extant literature which primarily uses data from industrialized countries.

4.5. Summary

In Study #2, we discussed a general model of within-country diffusion. By making certain modifications to existing models, we proposed a staged estimation procedure which provides insights which were not forthcoming using traditional approaches. By applying the staged estimation procedure, we could explain cross-national variances in diffusion via tests of various research hypotheses and obtain plausible parameter estimates for countries which have yet to undergo diffusion. Our application to the cellular industry (and Figure 5 in particular) reveals that the critical factor in explaining diffusion patterns across countries is the matched definition of social system size, S_i, and the adoption ceiling, c_i (i.e. the market potential), which must be estimated externally to the model (especially during the early phases of the international life cycle). This finding would suggest that greater research efforts be made to develop models which can assist managers in understanding and anticipating variances in the long-run ceiling across countries.

5. CONCLUDING REMARKS

This paper presents general models of global diffusion processes. We identify two processes: the timing of initial adoption at the country level (breadth - Study #1), and the within-country diffusion process (depth - Study #2). The models proposed for the two processes have the primary advantage of allowing researchers to rigorously test various hypotheses, whether generated by academicians or managers. This can reflect either exogenous or endogenous factors and can involve tests of potential linkages between innovation introduction timing and subsequent growth rates. We illustrate the application of our models to the cellular telephone industry across 184 countries.

Table 10 sheds light on the various components of global diffusion across Study #1 and Study #2. Though not our primary contribution, three substantive findings are noteworthy. First, we note that the impact of many factors (e.g. the effect of communism) is not uniform across the various components of global diffusion (e.g. strong effects for adoption timing, yet weak for growth rates). Other influences hypothesized in the diffusion literature have only marginal influence (e.g. number of competitors). Second, for other factors, the impact seems to be uniform in direction across all components. In particular, ethnic heterogeneity appears to have a negative influence on most aspects of international diffusion; income per capita has a generally positive influence; crude death rates have a negative influence. Finally, we find that endogenous cross-country influences are strong for innovation introduction timing, yet inconsequential for within-country diffusion patterns. Further empirical research should be undertaken to examine the extent to which these findings are generalizable to other industries. We strongly suspect that specific factors affecting innovation diffusion will be largely category specific (contrast, for example, the diffusion of nuclear submarines and the diffusion of tropical crop pesticide use), yet commonly governed by theories of diffusion as discussed in Section 2 of the paper.

Insert Table 10 about here

Finally, we want to point out that our discussion has ignored the potential use of the proposed modelling procedures in forecasting exercises (as our contribution is focussed on modelling, estimation and, to a lesser extent, substantive theory testing). This focus is in line with the conclusion of Mahajan, Muller and Bass (1990, p. 9) that "parameter estimation for diffusion models is primarily of historical interest; by the time sufficient observations have been developed for reliable estimation, it is too late to use the estimates for forecasting purposes". Still, it is interesting to know that earlier versions of the models have been used over the past 6 years by cellular-telephone manufacturers to forecast within-country diffusion patterns. Model-based projections are used as benchmarks which are compared against or combined with forecasts generated from local (country or regional) offices.

APPENDIX A

In a split-hazard specification, one explicitly allows for the fact that some countries may never 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 δ_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 δ 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:

$$LL = \Pi_{i=1}^{N} \{\delta \, [S_i(t_i-1) - S_i(t_i)]\}^{1-d_i} * \{(1-\delta) + \delta \, S_i(t_i-1)\}^{d_i} . \tag{A.1}$$

If all countries which will eventually adopt have the same λ_0, one can substitute equation (4) into (A.1) 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 let λ_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):

$$\begin{aligned} LL = \sum_{i=1}^{N} ln \{ & \frac{(\delta^{1-d_i} - \delta)\,(1+d_i)\, a^r}{[(1-d_i)B_i(t_i-1) + a]^r} - \frac{(\delta^{1-d_i} - \delta)\, a^r}{[(1-d_i)B_i(t_i) + a]^r} \\ & + \frac{\delta(1+d_i)a^r}{[B_i(t_i-1)+a]^r} - \frac{\delta \, a^r}{[B_i(t_i-1)+(1-d_i)e^{\beta X_i(t_i)+cD_i(t_i)}+a]^r} \}, \end{aligned} \tag{A.2}$$

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 δ by δ_i in (A.2), where

$$\delta_i = \frac{1}{[1+\exp(\alpha X_i)]} \qquad \text{(A.3)}$$

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).

APPENDIX B.
Summary of Staged Estimation Procedure, Across Countries (* signifies actual values)

		Stage 1			Stage 2	Stage 3
	Country	S_i (000's)	c_i	c_iS_i (000's)	a_i	b_i
1	Afghanistan	16,450	0.002	33	0.0001	0.004
2	Albania	3,335	0.002	6	0.0048	0.402
3	Algeria	26,022	0.032	833	0.0004 *	0.464
4	American Samoa	43	0.180	8	0.0079	0.458
5	Andorra	53	0.474	25	0.0045	0.458
6	Angola	8,668	0.005	44	0.0001	0.003
7	Antigua & Barbuda	64	0.089	6	0.0050	0.266
8	Argentina	32,664	0.105	3,430	0.0004 *	0.164
9	Australia	17,288	0.538	9,301	0.00002 *	0.464
10	Austria	7,666	0.459	3,519	0.0005 *	0.144
11	Bahamas	252	0.368	93	0.0022 *	0.417
12	Bahrain	537	0.257	138	0.0123 *	0.427
13	Bangladesh	116,601	0.002	175	0.0007	0.079
14	Barbados	255	0.299	76	0.0028	0.117
15	Belgium	9,922	0.417	4,137	0.0012 *	0.184
16	Belize	228	0.041	9	0.0054	0.275
17	Benin	4,832	0.005	24	0.0010	0.010
18	Bermuda	58	0.836	48	0.0144 *	0.155
19	Bhutan	1,598	0.012	19	0.0007	0.011
20	Bolivia	7,157	0.024	172	0.0116 *	0.111
21	Botswana	1,258	0.018	23	0.0005	0.217
22	Brazil	155,356	0.076	11,807	0.0010 *	0.462
23	Brunei	398	0.114	45	0.0331 *	0.274
24	Bulgaria	8,911	0.200	1,782	0.0007 *	0.083
25	Burkina Faso	9,360	0.002	18	0.0002	0.017
26	Burma	42,112	0.001	59	0.0006	0.046
27	Burundi	5,831	0.001	8	0.0018	0.015
28	Cambodia	7,146	0.001	7	0.0006	0.018
29	Cameroon	11,390	0.005	58	0.0001	0.034
30	Canada	26,835	0.668	17,926	0.0013 *	0.491
31	Cape Verde	387	0.006	2	0.0055	0.074
32	Cayman Islands	27	0.406	11	0.0091 *	0.376
33	Central African Rep	2,952	0.002	6	0.0002	0.006
34	Chad	5,122	0.001	7	0.00003	0.002
35	Chile	13,287	0.054	718	0.0079 *	0.389
36	China, People's Rep	1,151,487	0.005	5,757	0.0001 *	0.230
37	Colombia	33,778	0.073	2,466	0.0019	0.444
38	Comoros	477	0.009	4	0.0052	0.030
39	Congo	2,309	0.011	25	0.0005	0.035
40	Costa Rica	3,111	0.123	383	0.0008 *	0.458
41	Cote D'Ivoire	12,978	0.011	143	0.0011	0.064
42	Cuba	10,732	0.050	537	0.0015	0.353
43	Cyprus	709	0.253	179	0.0072 *	0.104
44	Czechoslovakia	15,725	0.221	3,475	0.0010 *	0.159
45	Denmark	5,133	0.702	3,603	0.0018 *	0.167
46	Djibouti	346	0.022	8	0.0014	0.009
47	Dominica	86	0.039	3	0.0088	0.299
48	Dominican Republic	7,385	0.029	214	0.0009 *	0.303

Appendix B. (continued)

	Country	Stage 1 S_i (000's)	c_i	c_iS_i (000's)	Stage 2 a_i	Stage 3 b_i
49	East Germany	16,705	0.206	3,441	0.0004	0.168
50	Ecuador	10,752	0.038	409	0.0028	0.279
51	Egypt	54,452	0.012	653	0.0008 *	0.157
52	El Salvador	5,419	0.025	135	0.0052 *	0.187
53	Equatorial Guinea	379	0.007	3	0.0006	0.013
54	Ethiopia	53,191	0.003	144	0.0001	0.023
55	Falkland Islands	2	0.211	0	0.0160	0.121
56	Fiji	744	0.075	56	0.0045	0.235
57	Finland	4,991	0.571	2,850	0.0008 *	0.183
58	France	56,596	0.537	30,392	0.0001 *	0.353
59	French Guiana	102	0.274	28	0.0032	0.275
60	French Polynesia	195	0.198	39	0.0040	0.266
61	Gabon	1,080	0.012	13	0.0011	0.021
62	The Gambia	875	0.005	5	0.0003	0.013
63	Germany (west)	79,548	0.572	45,501	0.0002	0.221
64	Ghana	15,617	0.006	95	0.0063 *	0.064
65	Greece	10,043	0.336	3,374	0.0012	0.142
66	Greenland	57	0.327	19	0.0009	0.466
67	Grenada	84	0.062	5	0.0038	0.206
68	Guadeloupe	345	0.174	60	0.0017	0.419
69	Guam	145	0.257	37	0.0074	0.374
70	Guatemala	9,266	0.013	120	0.0125 *	0.189
71	Guinea	7,456	0.002	13	0.0004	0.002
72	Guinea-Bissau	1,024	0.003	3	0.0004	0.008
73	Guyana	750	0.035	26	0.0036	0.147
74	Haiti	6,287	0.007	45	0.0022	0.015
75	Honduras	4,949	0.009	43	0.0141 *	0.353
76	Hungary	10,558	0.129	1,362	0.0073 *	0.068
77	Iceland	260	0.527	137	0.0088 *	0.315
78	India	866,352	0.004	3,812	0.0005	0.239
79	Indonesia	193,560	0.004	832	0.0008 *	0.450
80	Iran, I.R. of	59,051	0.051	312	0.0001	0.258
81	Iraq	19,525	0.043	840	0.0007	0.364
82	Ireland, Republic of	3,489	0.235	820	0.0001 *	0.180
83	Israel	4,477	0.380	1,701	0.0006 *	0.403
84	Italy	57,772	0.405	23,398	0.0001 *	0.295
85	Jamaica	2,489	0.059	147	0.0042	0.266
86	Japan	124,017	0.513	63,621	0.0001 *	0.462
87	Jordan	3,413	0.009	31	0.0034	0.530
88	Kenya	25,242	0.012	303	0.0026 *	0.257
89	Kiribati	71	0.015	1	0.0077	0.020
90	Kuwait	2,204	0.165	364	0.0275 *	0.553
91	Laos	4,113	0.002	9	0.0008	0.017
92	Lebanon	3,385	0.057	193	0.0021 *	0.133
93	Lesotho	1,801	0.004	8	0.0083	0.063
94	Liberia	2,730	0.004	11	0.0013	0.028
95	Libya	4,351	0.046	200	0.0039	0.404
96	Liechtenstein	28	0.810	23	0.0027	0.235
97	Luxembourg	388	0.544	211	0.0005 *	0.086
98	Macau	446	0.079	35	0.0199 *	0.212
99	Madagascar	12,185	0.004	52	0.0004	0.018

Appendix B. (continued)

	Country	Stage 1 S_i (000's)	Stage 1 c_i	Stage 1 $c_i S_i$ (000's)	Stage 2 a_i	Stage 3 b_i
100	Malawi	9,438	0.006	55	0.0006	0.006
101	Malaysia	17,982	0.066	1,187	0.0034 *	0.460
102	Maldives	226	0.005	1	0.0138	0.062
103	Mali	8,339	0.001	9	0.0001	0.003
104	Malta	356	0.300	107	0.0084 *	0.135
105	Martinique	345	0.211	73	0.0029	0.268
106	Mauritania	1,996	0.003	5	0.0004	0.007
107	Mauritius	1,081	0.048	52	0.0051	0.194
108	Mexico	90,007	0.086	7,741	0.0011 *	0.705
109	Monaco	30	0.990	30	0.0106	0.115
110	Mongolia	2,247	0.025	56	0.0018	0.180
111	Morocco	26,182	0.013	340	0.0006 *	0.236
112	Mozambique	15,113	0.004	67	0.0006	0.011
113	Namibia	1,521	0.049	75	0.0018	0.062
114	Nauru	9	0.213	2	0.0055	0.376
115	Nepal	19,612	0.001	22	0.0007	0.020
116	Netherlands	15,022	0.576	8,653	0.0007 *	0.304
117	Netherlands Antilles	184	0.168	31	0.0086	0.232
118	New Caledonia	172	0.221	38	0.0018	0.460
119	New Zealand	3,309	0.623	2,062	0.0009 *	0.395
120	Nicaragua	3,752	0.013	49	0.0018	0.256
121	Niger	8,154	0.002	15	0.0005	0.015
122	Nigeria	88,515	0.008	726	0.0007 *	0.106
123	Norway	4,273	0.579	2,474	0.0005 *	0.082
124	Oman	1,534	0.055	84	0.0089 *	0.153
125	Pakistan	117,490	0.005	611	0.0011 *	0.054
126	Panama	2,476	0.105	260	0.0027 *	0.337
127	Papua New Guinea	3,913	0.016	63	0.0027	0.074
128	Paraguay	4,799	0.024	115	0.0069 *	0.433
129	Peru	22,362	0.030	671	0.0119 *	0.316
130	Philippines	65,759	0.015	986	0.0005 *	0.327
131	Poland	37,800	0.105	3,969	0.0016 *	0.238
132	Portugal	10,388	0.169	1,756	0.0020 *	0.130
133	Puerto Rico	3,295	0.196	646	0.0008	0.466
134	Qatar	518	0.342	177	0.0156	0.398
135	Reunion	607	0.140	85	0.0029	0.417
136	Romania	23,397	0.093	2,176	0.0011	0.150
137	Rwanda	7,903	0.001	5	0.0021	0.017
138	Sahara, Western	197	0.006	1	0.0011	0.001
139	San Marino	23	0.367	8	0.0105	0.134
140	Sao Tome E Principe	128	0.022	3	0.0092	0.085
141	Saudi Arabia	17,870	0.152	2,716	0.0008 *	0.445
142	Senegal	7,953	0.007	58	0.0006	0.030
143	Seychelles	69	0.142	10	0.0054	0.140
144	Sierra Leone	4,275	0.005	21	0.0001	0.003
145	Singapore	2,756	0.369	1,017	0.0059 *	0.264
146	Solomon Islands	347	0.011	4	0.0090	0.337
147	Somalia	6,709	0.001	8	0.0018	0.026
148	South Africa	40,601	0.113	4,588	0.0001 *	0.316
149	South Korea	43,134	0.149	6,427	0.0003 *	0.391
150	Spain	39,385	0.350	13,785	0.000007 *	0.579

Appendix B. (continued)

	Country	Stage 1 S_i (000's)	Stage 1 c_i	Stage 1 c_iS_i (000's)	Stage 2 a_i	Stage 3 b_i
151	Sri Lanka	17,424	0.007	120	0.0042 *	0.338
152	St. Kitts and Nevis	40	0.055	2	0.0031	0.074
153	St. Lucia	153	0.067	10	0.0094	0.299
154	St. Vincent & the Gr	114	0.056	6	0.0055	0.234
155	Sudan	27,220	0.003	93	0.0002	0.037
156	Suriname	402	0.074	30	0.0026	0.194
157	Swaziland	859	0.023	20	0.0019	0.054
158	Sweden	8,564	0.830	7,108	0.0004 *	0.221
159	Switzerland	6,784	0.600	4,070	0.0012 *	0.238
160	Syrian Arab Republic	12,966	0.053	687	0.0033	0.443
161	Taiwan	20,659	0.209	4,318	0.0051 *	0.444
162	Tanzania	26,869	0.005	137	0.0006	0.022
163	Thailand	56,814	0.013	739	0.0020 *	0.378
164	Togo	3,811	0.004	17	0.0006	0.064
165	Tonga	102	0.037	4	0.0140	0.134
166	Trinidad & Tobago	1,285	0.095	122	0.0066	0.204
167	Tunisia	8,276	0.034	281	0.0002 *	0.473
168	Turkey	58,581	0.055	3,222	0.0006 *	0.349
169	Tuvalu	9	0.013	0	0.0089	0.038
170	Uganda	18,690	0.004	69	0.0002	0.024
171	United Arab Emirates	2,390	0.255	609	0.0230 *	0.306
172	United Kingdom	57,515	0.523	380	0.0021 *	0.100
173	United States	252,502	0.740	186,852	0.0005 *	0.437
174	Uruguay	3,121	0.116	362	0.0033 *	0.111
175	USSR (Former)	293,048	0.107	31,356	0.00002	0.236
176	Vanuatu	170	0.019	3	0.0172	0.299
177	Venezuela	20,189	0.088	1,777	0.0006 *	0.652
178	Vietnam	67,568	0.002	122	0.0004	0.234
179	Virgin Islands, US	99	0.390	39	0.0122	0.264
180	Western Samoa	190	0.037	7	0.0102	0.234
181	Yugoslavia	17,123	0.123	2,106	0.00001	0.437
182	Zaire	37,832	0.001	42	0.0096 *	0.071
183	Zambia	8,446	0.012	101	0.0004	0.071
184	Zimbabwe	10,720	0.032	343	0.0013	0.316
	Minimum	2	0.001	0	0.00001	0.001
	Maximum	1,151,487	0.990	186,852	0.03306	0.705
	Mean	29,273	0.150	3,128	0.00380	0.216
	Standard Deviation	111,958	0.208	15,450	0.00519	0.165

Note: The reported values in Stages 2 and 3 are based on the retained models in Table 9.

References

Amann, R. and J.M. Cooper (1982), *Industrial Innovation in the Soviet Union*, New Heaven: Yale University Press.

Antonelli, C. (1993), "Investment and Adoption in Advanced Telecommunications," *Journal of Economic Behavior and Organization*, 20, 227-245.

Bass, F.M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science*, 15, 215-227.

Berliner, J. (1976), *The Innovation Decision in the Soviet Industry*, Cambridge, Mass: MIT Press.

Bridges, E., A.T. Coughlan and S. Kalish (1991), "New Technology Adoption in an Innovative Marketplace: Micro- and Macro-level Decision Making Models," *International Journal of Forecasting*, 7, 257-270.

Chatterjee, R. and J. Eliashberg (1990), "Innovation Diffusion Process: A Micro-Modeling Approach," *Management Science*, 36, 1057-1079.

Dawar, N. and P.M. Parker (1994), "Marketing Universals: Consumers' Use of Brand Name, Price, Physical Appearance and Retailer Reputation as a Signal of Product Quality," *Journal of Marketing*, 58, 81-95.

Dekimpe, M.G. and D.G. Morrison (1991), "A Modeling Framework for Analyzing Retail Store Durations," *Journal of Retailing*, 67, 68-92.

Easingwood, C.J., V. Mahajan and E. Muller (1983), "A Nonuniform Influence Innovation Diffusion Model of New Product Acceptance," *Marketing Science*, 2, 273-296.

Flinn, C.J. and J.J. Heckman (1982), "New Methods for Analyzing Individual Event Histories," in S. Leinhardt (Ed.), *Sociological Methodology 1982*, San Francisco: Jossey-Bass, 99-140.

Gatignon, H., J. Eliashberg and T.S. Robertson (1989), "Modeling Multinational Diffusion Patterns: An Efficient Methodology," *Marketing Science*, 8, 231-247.

Gatignon, H. and T.S. Robertson (1985), "A Propositional Inventory for New Diffusion Research," *Journal of Consumer Research*, 11, 849-867.

Gönül, F. and K. Srinivasan (1993), "Consumer Purchase Behavior in a Frequently Bought Product Category: Estimation Issues and Managerial Insights from a Hazard Function Model with Heterogeneity," *Journal of the American Statistical Association*, 88, 1219-1227.

Gupta, S. (1991), "Stochastic Models of Interpurchase Time with Time-Dependent Covariates," *Journal of Marketing Research*, 28, 1-15.

Han, A. and J. Hausman (1990), "Flexible Parametric Estimation of Duration and Competing Risk Models," *Journal of Applied Econometrics*, 5, 1-28.

Hannan, T. and J.M. McDowell (1984), "The Determinants of Technology Adoption: The Case of the Banking Firm," *Rand Journal of Economics*, 15, 328-335.

Hanssens, D.M., L.J. Parsons and R.L. Schultz (1990), *Market Response Models: Econometric and Time Series Analysis*, Kluwer Academic Publishers.

Heckman, J. and B. Singer (1982), "Population Heterogeneity in Demographic Models," in K. Land and A. Rogers (Eds.), *Multidimensional Mathematical Demography*, 567-599.

Heckman, J. and B. Singer (1984), "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," *Econometrica*, 52, 271-320.

Heeler, R.M. and T.P. Hustad (1980), "Problems in Predicting New Product Growth for Consumer Durables," *Management Science*, 26, 1007-1020.

Helsen, K., Jedidi, K. and W.S. DeSarbo (1993), "A New Approach to Country Segmentation Utilizing Multinational Diffusion Patterns," *Journal of Marketing*, 57, 60-71.

Helsen, K. and D.C. Schmittlein (1993), "Analyzing Duration Times in Marketing: Evidence for the Effectiveness of Hazard Rate Models," *Marketing Science*, 11, 395-414.

Helsen, K. and D.C. Schmittlein (1994), "Understanding Price Effects for New Nondurables: How Price Responsiveness Varies Across Depth-of-Repeat Classes and Types of Consumers," *European Journal of Operations Research*, 76, 359-374.

Jain, D.C. and N. Vilcassim (1991), "Investigating Household Purchase Timing Decisions: A Conditional Hazard Function Approach," *Marketing Science*, 10, 1-23.

Kamakura, W.A. and S.K. Balasubramanian (1988), "Long-Term View of the Diffusion of Durables," *International Journal of Research in Marketing*, 5, 1-13.

Kiefer, N.M. (1988), "Analysis of Grouped Duration Data," in N.U. Prabhu (Ed.), *Statistical Inference from Stochastic Processes*, Providence: American Mathematical Society.

Lilien, G.L., P. Kotler and K.S. Moorthy (1992), *Marketing Models*, Englewood Cliffs, NJ: Prentice Hall.

Lindberg, Bertil C. (1982), "International Comparison of Growth in Demand for a New Durable Consumer Product," *Journal of Marketing Research*, XIX, August, 362-71.

Lancaster, T. (1990). *The Econometric Analysis of Transition Data.* Cambridge: Cambridge University Press.

Leary, N.A. and J. Thornton (1989), "Are Socialist Industries Inoculated Against Innovation? A Case Study of Technological Change in Steelmaking," *Comparative Economic Studies*, 31, 42-65.

Mahajan, V. and E. Muller (1994), "Innovation Diffusion in a Borderless Global Market: Will the 1992 Unification of the European Community Accelerate Diffusion of New Ideas, Products and Technologies," *Technological Forecasting and Social Change*, Forthcoming.

Mahajan, V., E. Muller and F.M. Bass (1990), "New Product Diffusion Models in Marketing: A Review and Directions for Research," *Journal of Marketing*, 54, 1-26.

Mahajan, V., E. Muller and R.K. Srivastava (1990), "Using Innovation Diffusion Models to Develop Adopter Categories," *Journal of Marketing Research*, 27, 37-50.

Mahajan, V. and R.A. Peterson (1979), "Integrating Time and Space in Technological Substitution Models," *Technological Forecasting and Social Change*, 14, 231-241.

Manton, K. G., E. Stallard and J.W. Vaupel (1986), "Alternative Models for the Heterogeneity of Mortality Risks Among the Aged," *Journal of the American Statistical Association*, 82, 635-644.

Mansfield, E. (1968), *Industrial Research and Technological Innovation: An Econometric Analysis*, New York: W.W. Norton and Co.

Meyer, B.D. (1986), "Semiparametric Estimation of Hazard Models," Working Paper, MIT.

Meyer, B.D. (1990), "Unemployment, Insurance and Unemployment Spells," *Econometrica*, 58, 757-782.

Ohmae, Kenichi (1990), "The Borderless World," New York: Harper Business.

Parker, P.M. (1992), "Price Elasticity Dynamics over the Adoption Life Cycle," *Journal of Marketing Research*, 29, 358-367.

Ridder, G. (1986), "The Sensitivity of Duration Models to Misspecified Unobserved Heterogeneity and Duration Dependence," Working Paper, University of Amsterdam.

Robertson, T.S. (1967), "*Determinants of Innovative Behavior*," in R. Moyer (Ed.), Proceedings of the American Marketing Association, Chicago: American Marketing Association, 328-332.

Robertson, T.S. (1971), *Innovative Behavior and Communication*, New York: Holt, Rinehart and Winston.

Rogers, E.M. (1983), *Diffusion of Innovations*, New York: The Free Press.

Schmittlein, D.C. and V. Mahajan (1982), "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance," *Marketing Science*, 1, 57-78.

Sharma, S. (1993), "Behind the Diffusion Curve: An Analysis of ATM Adoption," Working Paper, Department of Economics, UCLA.

Sharma, S. and R.K. Sinha (1991a), "Firm Characteristics, Market Structure and the Dynamics of Technology Diffusion: A Semiparametric Econometric Model," Working Paper, Department of Economics, UCLA.

Sharma, S. and R.K. Sinha (1991b), "Firm Characteristics and the Diffusion of Information Technology," Working Paper, Department of Economics, UCLA.

Simon, H. (1989), *Price Management*, North Holland, Elsevier Science Publishers: Amsterdam.

Simon, H. (1994), "Marketing Science's Pilgrimage to the Ivory Tower," in G. Laurent, G. Lilien and B. Pras (Eds.), *Research Traditions in Marketing*, Kluwer Academic Publishers, 27-43.

Sinha, R.K. and M. Chandrashekaran (1992), "A Split Hazard Model for Analyzing the Diffusion of Innovations," *Journal of Marketing Research*, 24, 116-127.

Srinivasan, V. and C.H. Mason (1986), "Nonlinear Least Squares Estimation of New Product Diffusion Models," *Marketing Science*, 5, 169-178.

Takada, H. and D. Jain (1991), "Cross-National Analysis of Diffusion of Consumer Durable Goods in Pacific Rim Countries," *Journal of Marketing*, 55, 48-54.

Tigert, D. and B. Farivar (1981), "The Bass New Product Growth Model: A Sensitivity Analysis for a High Technology Product," *Journal of Marketing*, 45, 81-90.

Trussell, J. and T. Richards (1985), "Effects of Labor Market Structure on Job Shift Patterns," in J.J. Heckman and B. Singer (Eds.), *Longitudinal Analysis of Labor Market Data*, Cambridge: Cambridge University Press, 327-363.

Van de Gucht, L.M. (1994), "Leveraged Buyouts: An Empirical Examination of the Decision to Return to Public Status," Unpublished Ph.D. Dissertation, University of South Carolina.

Vilcassim, N. and D.C. Jain (1991), "Modeling Purchase Timing and Brand-Switching Behavior Incorporating Explanatory Variables and Unobserved Heterogeneity," *Journal of Marketing Research*, 28, 29-41.

Vanhuele, M., M.G. Dekimpe, S. Sharma and D.G. Morrison (1994), "Probability Models for Duration: The Data Don't Tell the Whole Story," *Organizational Behavior and Human Decision Processes*, Forthcoming.

Table 1. Summary of Recent International Diffusion Studies

Study	Number of Countries	Breadth of Adoption	Depth of Adoption: Sample Matching	Depth of Adoption: Left-Hand Truncation Bias	Depth of Adoption: Exogenous Covariates	Depth of Adoption: Endogenous Covariates (Linkage)
Gatignon et al. (1989)	14	No	No	Yes	3	None
Heeler and Hustad (1980)	16	No	No	Yes	0	None
Helsen et al. (1993)	12	No	No	No	6	None
Lindberg (1982)	7	No	No	No	0	None
Mahajan and Muller (1994)	16	No	No	Yes	0	Yes (No)
Takada and Jain (1991)	4	No	No	Partial	1	Yes (No)
Present study	184	Yes	Yes	No	8	Yes (Yes)

Table 2. Countries Compared within International Marketing Studies

Number of Countries	Number of Studies	%
50 <	1	0.9
30 - 50	1	0.9
20 - 30	4	3.6
10 - 20	12	10.8
6 - 9	17	15.3
3 - 5	39	35.1
2	37	33.3
Total	111	100%

Note: Journals surveyed (1975-1993):
Journal of International Business Studies
European Journal of Marketing
The Columbia Journal of World Business
Journal of Business Research
Journal of Marketing
International Marketing Review
Journal of the Academy of Marketing Science
International Journal of Research in Marketing
Journal of Advertising Research
Journal of Consumer Research
Journal of Global Marketing
Journal of Advertising
International Journal of Advertising
Journal of Marketing Research
Journal of the Market Research Society
Marketing and Research Today
Industrial Marketing Management
Journal of Consumer Affaires
Journal of Economic Psychology
Journal of Macromarketing
Journal of Product Innovation Management
Marketing Science
Journal of Public Policy and Marketing
Management Science
Marketing Letters

Table 3. Diffusion of Cellular Services Across Countries

Innovator (4%)
Denmark
Finland
Indonesia
Japan
Norway
Saudi Arabia
Spain
Sweden

Early Adopter (12%)
Australia
Austria
Bahrain
Canada
France
Germany (west)
Iceland
Ireland, Republic of
Israel
Italy
Kuwait
Luxembourg
Malaysia
Netherlands
Oman
South Africa
South Korea
Thailand
Tunisia
Turkey
United Kingdom
United States

Early Majority (33%)
Algeria
American Samoa
Argentina
Bahamas
Bangladesh
Belgium
Bermuda
Bolivia
Botswana
Brazil
Brunei
Bulgaria
Cayman Islands
Chile
China, People's Rep
Colombia
Costa Rica
Cyprus
Czechoslovakia
Dominican Republic
Ecuador
Egypt
El Salvador
Fiji
Gabon
Ghana
Greece
Guatemala
Honduras
Hungary
India
Kenya
Laos
Lebanon
Macau
Malta
Mauritius
Mexico
Morocco
New Zealand
Nigeria
Pakistan
Panama
Paraguay
Peru
Philippines
Poland
Portugal
Romania
Singapore
Sri Lanka
St. Kitts and Nevis
Switzerland
Taiwan
Tonga
Trinidad & Tobago
Uruguay
Venezuela
Vietnam
Zaire

Late Majority and Laggards (51%)	
Afghanistan	Malawi
Albania	Maldives
Andorra	Mali
Angola	Martinique
Antigua & Barbuda	Mauritania
Barbados	Monaco
Belize	Mongolia
Benin	Mozambique
Bhutan	Namibia
Burkina Faso	Nauru
Burma	Nepal
Burundi	Netherlands Antilles
Cambodia	New Caledonia
Cameroon	Nicaragua
Cape Verde	Niger
Central African Rep	Papua New Guinea
Chad	Puerto Rico
Comoros	Qatar
Congo	Reunion
Cote D'Ivoire	Rwanda
Cuba	Sahara, Western
Djibouti	San Marino
Dominica	Sao Tome E Principe
East Germany	Senegal
Equatorial Guinea	Seychelles
Ethiopia	Sierra Leone
Falkland Islands	Solomon Islands
French Guiana	Somalia
French Polynesia	St. Lucia
Greenland	St. Vincent & the Gr
Grenada	Sudan
Guadeloupe	Suriname
Guam	Swaziland
Guinea	Syrian Arab Republic
Guinea-Bissau	Tanzania
Guyana	The Gambia
Haiti	Togo
Iran, I.R. of	Tuvalu
Iraq	Uganda
Jamaica	United Arab Emirates
Jordan	USSR (Former)
Kiribati	Vanuatu
Lesotho	Virgin Islands, US
Liberia	Western Samoa
Libya	Yugoslavia
Liechtenstein	Zambia
Madagascar	Zimbabwe

Time

Table 4: 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 5. 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
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
No. of Competing Systems	1.0	0.5	1.0	4.0
Social System Factors				
No. of Ethnic Groups	5.0	2.6	1.0	15.0

Table 6. Parameter Estimates for the Cross-country Timing Model

	Model 1	Model 2	Model 3	Model 4
λ_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 Countries	-	-	-	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; significance levels are determined using likelihood-ratio tests
Model 1: 184 countries - only exogenous covariates - with gamma mixing
Model 2: 184 countries - only exogenous covariates - without gamma mixing
Model 3: 156 countries - only exogenous covariates - with gamma mixing
Model 4: 156 countries - exogenous and endogenous covariates - with gamma mixing

Table 7. **Estimated Bass-Model Coefficients Across Countries using Nonlinear Estimation**

		External Influence		Internal Influence		Potential		Adjusted
Countries	DF	a	P-Value	b	P-Value	M	P-Value	R-sq
Algeria	3	0.0115	1.00	1.91	1.00	47	1.00	0.98
Argentina	4	0.0008	1.00	0.84	0.63	5,611	1.00	0.73
Australia	7	0.0310	0.12	0.91	1.00	531	0.00	0.90
Austria	9	0.0056	0.60	0.55	0.02	305	0.14	0.83
Bahamas	5	9.3078	1.00	-0.09	1.00	30,981	1.00	-0.09
Bahrain	6	0.0000	1.00	-0.26	0.37	69,253	1.00	-0.16
Belgium	6	0.0012	1.00	0.05	0.97	7,325	1.00	-0.45
Bermuda	4	0.0003	1.00	-0.49	0.31	1,884	1.00	0.65
Brunei	4	0.0000	1.00	-0.23	0.89	58,587	1.00	-0.98
Canada	8	0.0000	1.00	0.30	0.30	-575,682	1.00	0.79
Cayman Islands	6	0.0000	1.00	0.00	1.00	4,472	1.00	-0.21
Chile	4	0.0000	1.00	0.45	0.63	108,164	1.00	0.79
China, People's Rep.	6	0.0181	0.98	0.29	0.92	362	0.98	-0.45
Costa Rica	4	0.0007	1.00	0.44	0.56	540	1.00	0.86
Cyprus	4	0.0004	1.00	0.09	0.96	3,505	1.00	-0.61
Denmark*	11	0.0189	0.01	0.24	0.00	416	0.02	0.86
Dominican Republic	6	-1.2857	1.00	0.36	0.67	-168,234	1.00	0.44
Egypt	6	1.1538	1.00	0.32	0.50	410,673	1.00	0.72
Finland	11	0.0062	0.53	0.62	0.00	434	0.00	0.96
France	8	0.0000	1.00	0.33	0.39	-381,546	1.00	0.71
Iceland	7	0.0053	1.00	-0.01	1.00	394	1.00	-0.49
Indonesia	10	-8.2635	1.00	0.36	0.11	-82,022	1.00	0.84
Ireland, Republic of	8	0.0000	1.00	0.44	0.50	-69,748	1.00	0.60
Israel	7	0.0105	0.31	1.10	0.00	31	0.00	0.98
Italy	8	0.0107	0.69	1.91	0.00	731	0.00	0.90
Japan	13	-0.0052	0.49	0.94	0.00	2,652	0.00	0.95
Kuwait	5	0.0000	1.00	-1.08	0.43	164,216	1.00	0.08
Luxembourg	8	5.4044	1.00	0.41	0.17	56,820	1.00	0.83
Macau	5	2.4262	1.00	0.38	0.80	313,990	1.00	-0.07
Malaysia	8	0.0000	1.00	0.37	0.38	-391,401	1.00	0.69
Malta	3	0.0008	0.00	0.12	1.00	1,408	1.00	0.46
Mexico	4	0.0870	0.42	0.86	0.25	307	0.17	0.78
Morocco	6	7.9281	1.00	0.34	1.00	217,279	0.00	-0.10
Netherlands*	8	0.0078	0.06	0.49	0.00	509	0.10	0.98
New Zealand	6	0.0296	0.86	0.33	0.69	292	0.87	0.09
Norway*	12	0.0241	0.10	0.36	0.01	327	0.00	0.49
Oman	7	5.4432	1.00	0.85	0.48	519,471	1.00	0.27
Pakistan	3	0.0020	1.00	0.07	1.00	1,264	1.00	0.34
Philippines	6	0.0000	1.00	0.36	0.92	-62,896	1.00	-0.30
Portugal	4	0.0000	1.00	0.28	0.70	316,027	1.00	0.73
Saudi Arabia	11	-0.0006	1.00	-0.04	0.84	-3,346	1.00	0.01
Singapore	5	0.0180	0.94	0.36	0.71	632	0.94	0.33
South Africa	7	0.0055	0.99	0.20	0.91	199	0.99	-0.38
South Korea	9	-1.9712	1.00	0.68	0.20	-3,071,661	1.00	0.79
Spain	11	-1.8815	1.00	0.77	0.00	-1,319,390	1.00	0.96
Sri Lanka	4	0.0000	1.00	0.00	1.00	10,001	1.00	0.00
Sweden	12	0.0002	0.97	0.67	0.00	751	0.00	0.92
Switzerland	6	0.0143	0.95	0.22	0.76	1,688	0.95	0.12
Taiwan	4	-0.0009	1.00	0.28	0.93	-54,539	1.00	-0.71
Thailand	7	0.0086	0.88	1.26	0.04	200	0.00	0.57
Tunisia	7	-9.0763	1.00	0.40	0.68	-15,459	1.00	0.27
Turkey	7	0.0000	1.00	0.49	0.21	196,179	1.00	0.83
United Arab Emirate	4	0.0009	1.00	-0.16	0.88	13,393	1.00	-0.54
United Kingdom	8	0.0560	0.26	0.27	0.55	1,893	0.25	-0.05
United States*	9	0.0094	0.08	0.67	0.00	14,134	0.00	0.98
Venezuela	4	0.0000	1.00	4.37	0.60	156,690	1.00	0.64
Zaire	5	0.0006	1.00	-0.19	0.78	589	1.00	-0.19
Average		0.1678	0.83	0.45	0.54	-61,417	0.74	0.37
Standard Deviation		2.5832	0.32	0.72	0.37	471,265	0.42	0.54

Note: DF= degrees of freedom; figures are rounded

* : countries with plausible and significant coefficients

Table 8. Applications of the Naive Pooled Model (nonlinear least square estimation)

Model	a_i	b_i	c_i	S_i	c_iS_i	SSE	MSE	R_a^2
Model 1:	0.0005 (N.S.)	0.56	---	---	18,679	1.3	57.4	0.93
Model 2	-0.0019	$1.11e^{-11}$	0.06	S	0.06 S	2.1	72.5	0.88
Model 3	0.0007	0.40	1.0 fixed	S	S	1.8	66.0	0.90
Model 4	0.0017	0.34	C	S	CS	1.1	52.9	0.94

Note: S signifies the vector variable of population sizes, across countries;
C signifies the vector variable of ceilings, across countries.
(N.S.) signifies "Not significant" (*p-value* = .73); all other estimates *p-value* < .001.

Table 9. Logistic Models of External and Internal Influences

Covariate	External Influences a_i		Internal Influences b_i	
	Full	Retained	Full	Retained
Exogeneous Factors				
Demographic Factors				
Avg. Annual Pop. Growth Rate	0.174**	0.165**	0.118	-
No. of Major Population Centers	-0.850***	-1.027***	0.559**	0.509***
Economic Factors				
GNP per Capita ($000)	0.142	-	0.180	-
Crude Death Rate	-0.769**	-0.797**	-1.330***	-1.274***
Communism	0.174	-	0.018	-
No. of Competing Systems	0.202*	0.195*	-0.059	-
Social System Factors				
No. of Ethnic Groups	-0.565*	-0.737**	-1.045***	-0.637***
Endogenous factors				
No. of other Countries Adopted	0.313	-	-0.099	-
Proportion World Bank Countries	-0.024	-	0.223	-
Fit SSE	0.0009	0.00095	1205976	1222751
Root MSE	0.0037	0.0037	55.12	55.08
R_a^2	0.67	0.68	0.9325	0.9326

Note: * < 0.1
** < 0.01
*** <0.001

Table 10. Degree of Covariate Influence on Global Diffusion Patterns: Strength and Direction

Covariate	Introduction Timing		Initial Penetration		Penetration Growth		Penetration Ceiling	
Exogeneous Factors								
Demographic Factors								
Avg. Annual Pop. Growth Rate	ns		**	(+)	ns		**	(-)
No. of Major Population Centers	***	(+)	***	(-)	**	(+)	***	(+)
Economic Factors								
GNP per Capita	***	(+)	ns		ns		***	(+)
Crude Death Rate	**	(-)	**	(-)	***	(-)	ns	
Communism	***	(-)	ns		ns		ns	
No. of Competing Systems	n/a		*	(+)	ns		*	(+)
Social System Factors								
No. of Ethnic Groups	*	(-)	**	(-)	***	(-)	ns	
Endogenous Factors								
Proportion World Bank Countries	*	(+)	ns		ns		n/a	
No. of Other Countries Adopted	n/a		ns		ns		n/a	

Notes: *: < 0.1; ** < 0.01; ***: < 0.001; ns: not significant; n/a: signifies not applicable;
Relations shown under penetration ceiling are based on bi-variate Pearson correlations

Figure 1. Worldwide Adoptions of Cellular Subscriptions

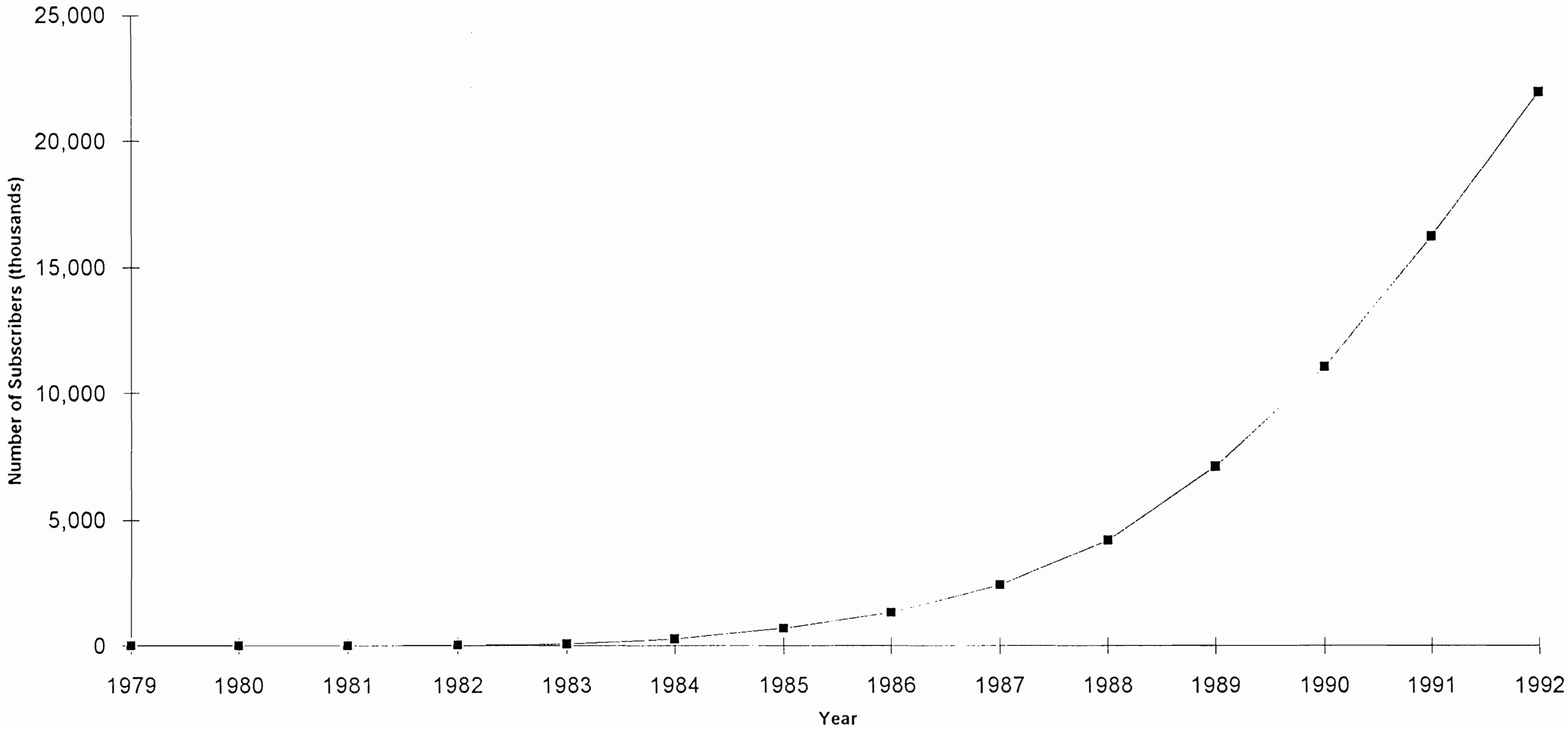
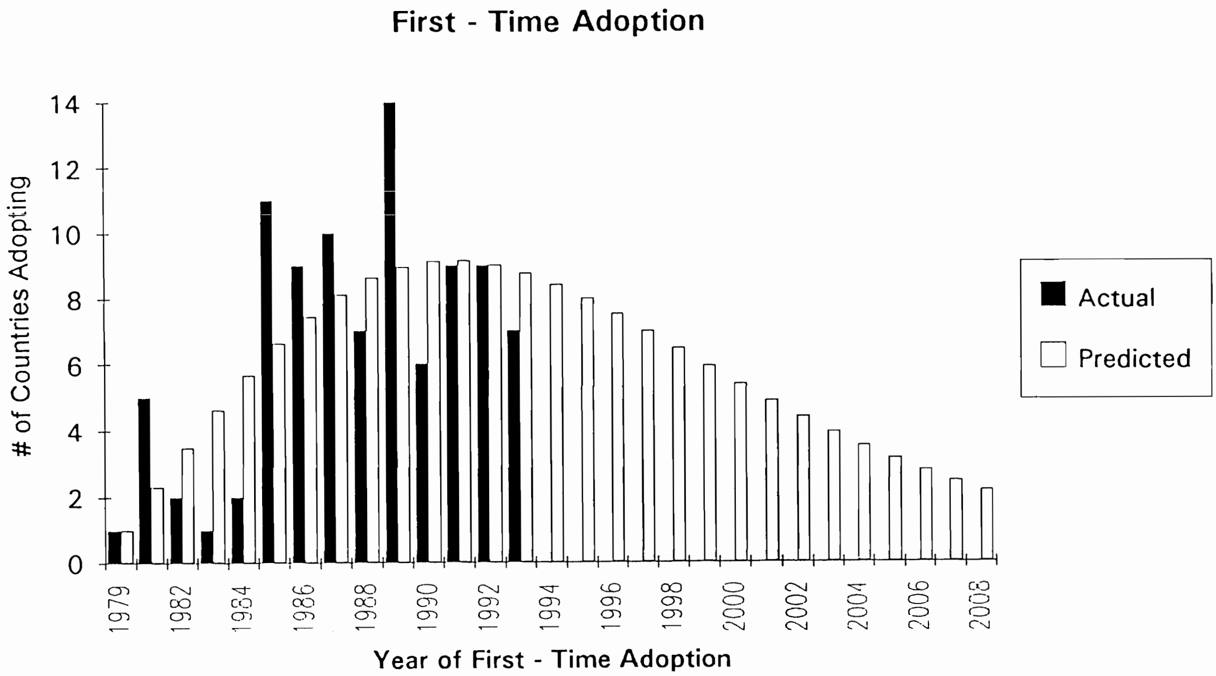
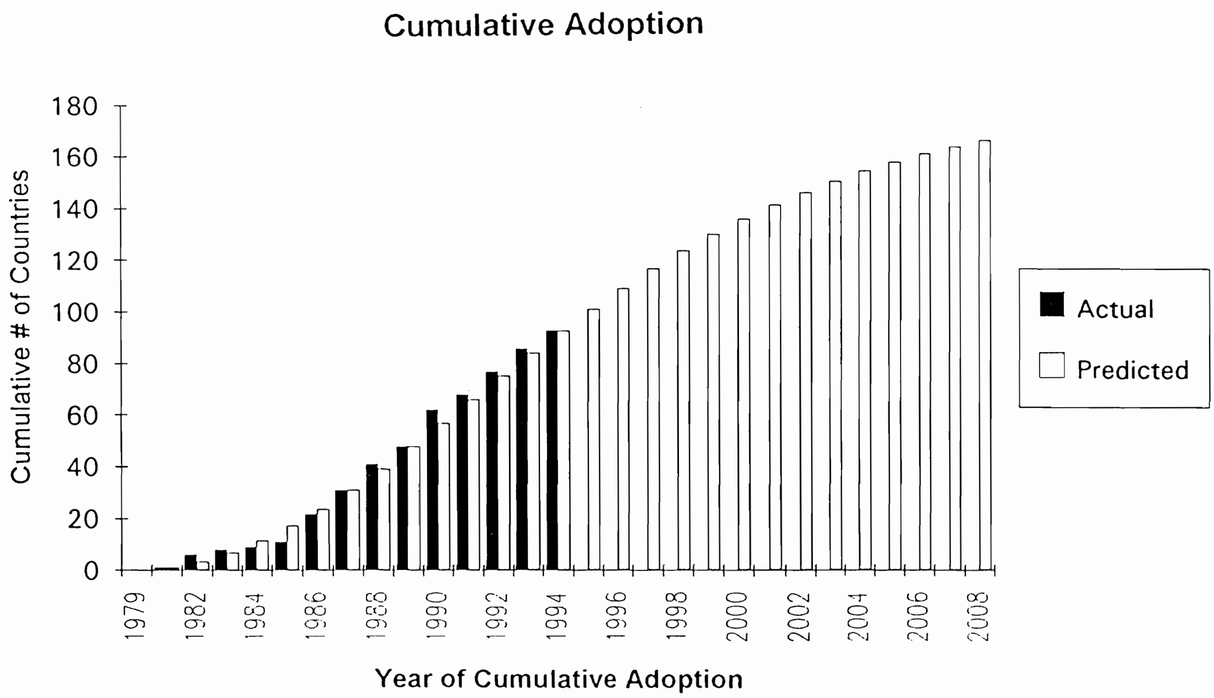


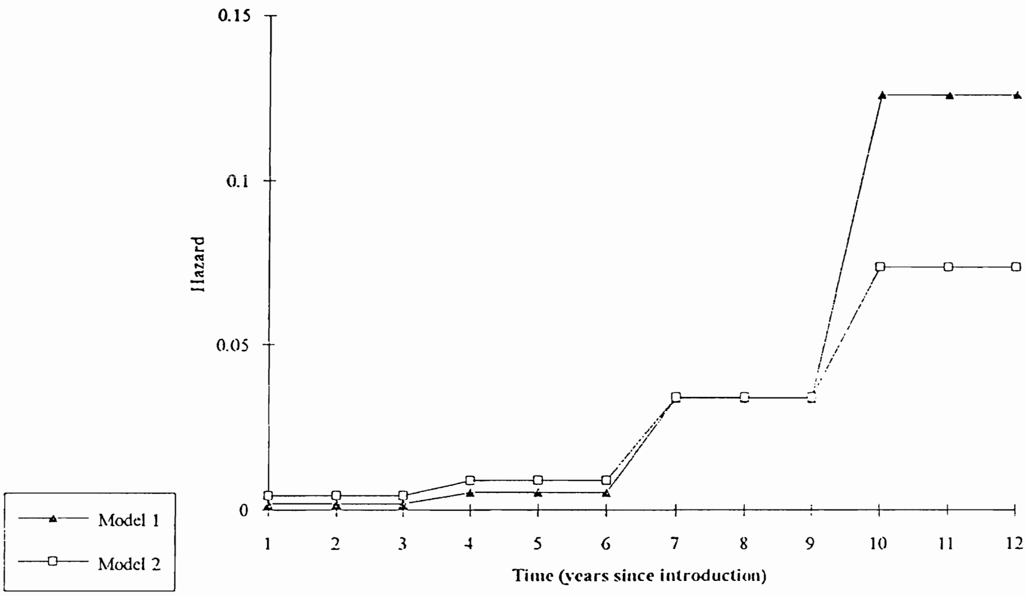
Figure 2. Country Adoption of Cellular Telephone Systems





Note: Predicted values are based on the application of the aggregate diffusion model proposed by Easingwood, Mahajan and Muller (1983).

Figure 3. Evolution of the Conditional Adoption Probability



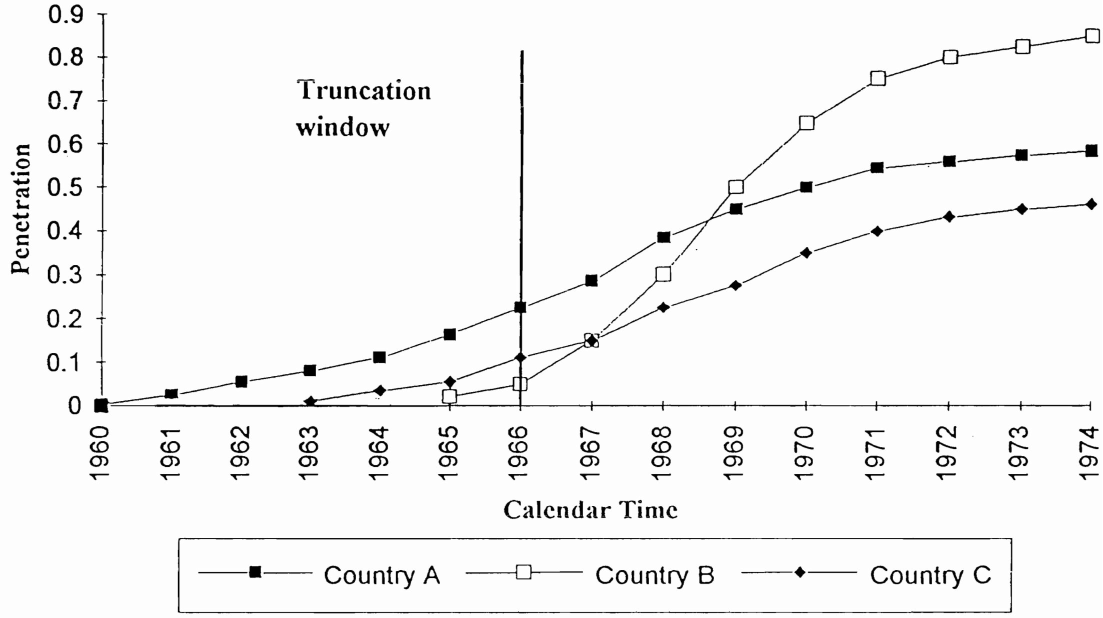
Note: The "average" non-communist country considered has a GNP per Capita of 5,065, a crude death rate of 9.4, 5 ethnic groups and 8 major population centers

Model 1: with correction for unobserved heterogeneity

Model 2: without correction for unobserved heterogeneity

Figure 4. Left-hand Truncation Bias

Diffusion curves not adjusted to comparable origin



Diffusion curves adjusted to comparable origin

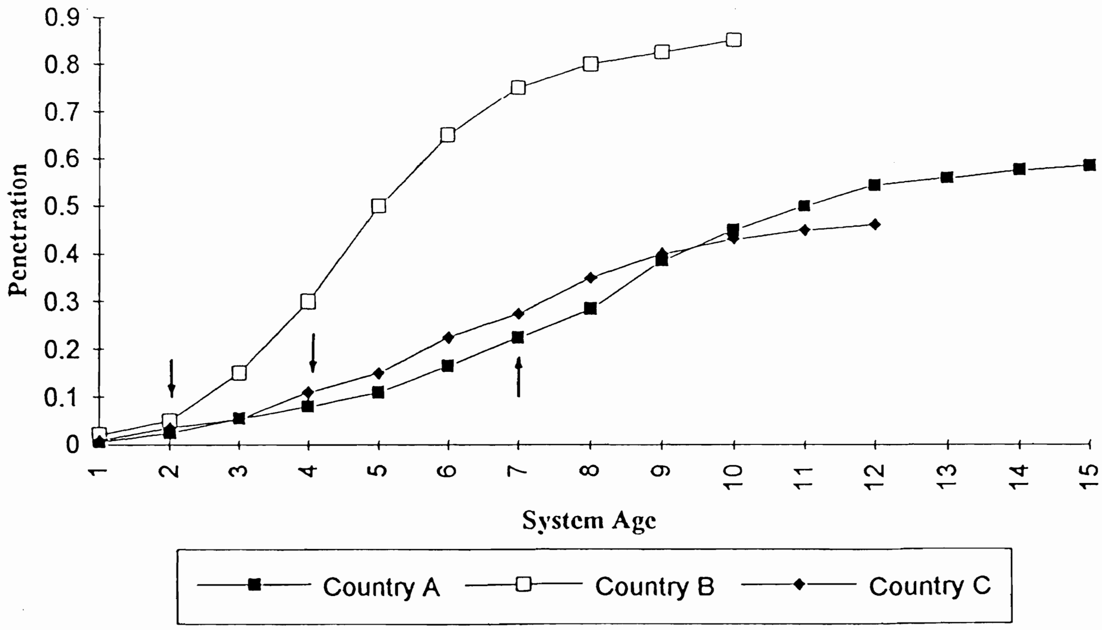


Figure 5. Penetration of Cellular Services, Across Countries