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Comparing adoption patterns: a global approach

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Comparing Adoption Patterns: A Global Approach

Abstract

New product diffusion models are "risky and potentially misleading" (Simon 1994, p. 14). This paper proposes a method which overcomes a number of problems associated with new product diffusion models noted in the marketing literature. We illustrate the methodology in the context of better understanding global variances in new product adoption. Building on existing diffusion models and sample *matching* principles from international consumer research, we suggest a "staged estimation procedure". The procedure provides both "sensible" and robust estimates, and remains implementable even if the diffusion process is in its earliest stage in most or all countries. In an empirical illustration covering 184 countries on five continents, we use cellular diffusion data to gain insights on how exogenous/endogenous country characteristics affect country-level diffusion patterns.

"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).

INTRODUCTION

While several new-product diffusion models have been developed and documented in the marketing literature since the 1960s, a number of authors have criticized their usefulness in applied settings. Heeler and Hustad (1980) were early to note the failure of Bass-type models to fit a wide variety of international diffusion data. Similarly, Schmittlein and Mahajan (1982) suggest that diffusion models typically require 10 or more observations to generate reasonable parameter estimates (or the data must cover periods beyond the penetration curve's inflection point). Even though their data series had 15 degrees of freedom each, Gatignon et al. (1989) report that almost 30 percent of their models yielded completely implausible estimates. In their review, Mahajan, Muller and Bass (1990, p. 9) note 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". Referring to the Bass model and its derivatives, Simon (1994, p. 14) goes the farthest by reporting that his experience with these models indicates that their applied use is "risky and potentially misleading".

It is not difficult to demonstrate the validity of these criticisms. Consider, for example, the comparison of cellular telephone diffusion patterns across countries. On an a priori basis, we would expect this category to be a "natural fit" for one to use the Bass model to explain cross-national variances in adoption patterns. Using diffusion parameters estimated in some countries, we might be able to expect, or model, likely diffusion patterns in others. Using diffusion data between 1979 and 1992 for over 70 countries, Table 1 reports parameter estimates resulting from nonlinear least squares estimation (see Srinivasan and Mason 1986) of the model proposed by Bass (1969). Since service started in different years across countries, the degrees of freedom from one country to another vary between 1 year and 13 years. Only 57 countries had sufficient degrees of freedom (i.e. at least 3 data points) to estimate the model. In almost 95 percent of the cases,[1]

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

implausible results (wrong signs or insignificant results) were obtained, which obviously would prevent subsequent analyses to explain variances across countries: (1) the external influence coefficient, a, is either greater than one or negative in 14 cases, (2) the internal influence coefficient, b, is either greater than one or negative in another 14 cases, (3) the market potential parameter, M, is negative in another 12 cases and the average across countries is also negative. These implausibilities are independent of the number of observations present (i.e. even countries having high degrees of freedom have implausible parameter estimates). Furthermore, even when countries have plausible "statistical" parameters, the estimates obtained lack face validity; for example, the long run market potential for the United States is 14 million, whereas the long run potential for Morocco is 217 million (Morocco has a population of less than 30 million persons and the United States has a population of over 250 million persons). Across the 57 countries, in no case did the Bass model produce reasonable results.

The primary contribution of this paper is methodological. Despite the apparent accumulation of evidence in support of the conclusion that the Bass model requires too many observations to be useful, or, even after estimation, is risky and misleading, we will demonstrate that these conclusions are more a function of the philosophical approach and estimation procedures used than of the intrinsic quality of the models themselves. We propose a "matched" estimation procedure which (1) results in plausible and superior estimates to traditional estimation approaches, (2) provides sufficient flexibility to explain cross-country variation using either exogenous or 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). The estimation procedure relies on a long held belief in cross-cultural consumer research that samples be *matched* on external criteria before valid comparisons be made. *Matching* procedures considerably attenuate Simon's criticism, and demonstrate the usefulness of Bass-type models in applied settings even if the innovation is in the earliest stages of its life-cycle in most countries.[2]

Our secondary contribution involves the scope of cross-cultural variation considered. The marketing of globalized products creates a number of challenges to firms hoping to serve

[2] While our discussion focuses on cross-cultural aspects of diffusion, our methodology equally applies to problems in comparing diffusion patterns across products within a given social system or country.

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. With the *matched* estimation procedure, we are given the opportunity to explore 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. Previous research on international diffusion has mainly dealt with comparisons of diffusion rates across a limited set of industrialized countries (see Table 2). 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[3]. This tendency to focus on only a few countries is mirrored in a broader survey of the international marketing literature. Table 3 shows that of 111 empirical international marketing studies published between 1975 and 1993 in 25 major marketing and management journals, only one reported a sample exceeding 50 countries. In this paper, we investigate adoption patterns across countries located in Africa (55 countries), Asia (37 countries), Europe (32 countries), the Americas (45 countries) and other regions (15, mostly island, countries).[4] In view of marketing's recent focus on empirical generalizations, considering a larger set of countries is important if one seeks to obtain general relationships to explain country diffusion patterns. Considering only a subset of countries (e.g. only industrialized nations) may lead to conclusions that are not generalizable to the rest of the world.

Working on global datasets provides, therefore, a unique opportunity to test global research hypotheses as it ensures the largest possible variation in both the dependent and the independent variables. For example, we will examine how a country's "innovativeness" (initial launch date or adoption timing) influences the subsequent speed of diffusion within the country. Studies having limited numbers of countries, simply lack the degrees of freedom and variance to consider this issue on a global basis (i.e. do not include innovators, early adopters, early majority, and laggard

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[3] Some of these countries were considered in Heeler and Hustad (1980), still the number of countries they considered was less than twenty.

[4]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).

countries).[5] Similarly, having a global focus gives researchers far more variance in exogenous factors likely to affect diffusion patterns. Though exploratory in this regard, 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, and levels of competition. We must qualify our contribution, however, since we use only one industry as an illustration. We do not, therefore, claim that the results are generalizable to every other product category; still, they represent a first attempt at testing certain prevailing theories on a global basis.

Our discussion will proceed as follows. First, we discuss the importance of sample *matching* in international diffusion research and define the four distinct components that identify a diffusion pattern. We argue that sample matching is required, even if the Bass model can be estimated with high statistical significance. We illustrate our alternative modeling approach and test various research hypotheses across 184 countries using diffusion data from the cellular telephone industry. In the final section we draw conclusions and present areas for future research.

MATCHED vs. *UNMATCHED* APPROACHES

To motivate our approach, we will now point to paradoxes presented by research attempting to compare diffusion processes as modeled by Bass (1969) or by similar diffusion models, even if these can be estimated with perfect reliability. Consider the following examples:

> ***Example #1.*** Consider two different countries (say the United States and Belgium) and assume that they have identical observed sales data (e.g. the exact same number of cellular subscribers for each year, over time for all points in time). A traditional application of the Bass model on these data would provide identical diffusion curve parameter estimates for both countries. Assume further that the fit statistics are extremely high and that all parameters are significant and plausible. A superficial interpretation of these results would lead to the conclusion that the diffusion process is identical in the two countries (i.e. both exhibit the same level of innovative behavior/external influence, imitative behavior/internal influence, or long run potential). Clearly, however, citizens of the smaller country (i.e. Belgium, with a population of less than 10 million) are manifestly more "innovative" than citizens of the larger country (i.e. the United States with over 250 million citizens). Similarly, even in cases where diffusion parameters are greater in one country (e.g. the U.S.) than another (e.g. Belgium), it still may be that the country with the smaller parameters is more "innovative"; of course, the converse as well, may be true. In essence,

[5] Some (indirect) evidence of such endogenous influences is found in Takada and Jain (1991), who find 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.

diffusion parameters are not intrinsically comparable, even if they can be estimated with high statistical significance, without an ***external frame*** of reference.

> **Example #2.** Consider the example of two countries of identical population sizes with identical diffusion patterns (e.g. number of cellular telephone subscribers for each year following the introduction of the service in each country respectively). Assume that the first country started the adoption process in 1970 whereas the second country started it only in 1980. If we use a common observation time window (e.g. 1982 to 1996) to estimate both diffusion curves, the resulting parameter estimates will differ even though the two actual patterns are identical. Again, without the ***external*** imposition of a time origin, inferences across models is impossible.

The two examples highlight fundamental problems in comparing diffusion model parameters across countries, even if these can be estimated with high degrees of confidence: *comparisons lack* ***externally valid*** *benchmarks*.

In order to make valid comparisons across diffusion patterns, what we define as a *matched approach* requires that researchers implement a system of "sample *matching*" procedures which make comparable the units of observation across countries. In doing so we directly follow recommendations on cross-cultural studies provided in Dawar and Parker (1994), Douglas and Craig (1983), Kale and Sudharshan (1987), Levitt (1983), Sheth (1986) and Simmonds (1985) among others. By *matching* samples or "social systems" on a set of external criteria, one seeks to minimize extraneous or unmeasurable covariates that might pollute analyses of variance. As indicated in Dawar and Parker (1994, p. 82):

> "Which matching criteria are used will depend on the category studied, but will most likely include economic criteria (wealth, professional status) and/or demographic criteria (age, marital status, lifestyle, family size) that characterize specific segments (Anderson and Engledow 1977; Engledow, Thorelli and Becker 1975; Katona, Strumpel and Zahn 1973). For example, we would sample doctors for medical products, engineers for technical industrial products, and farmers for agricultural products; samples drawn should be representative of the segments targeted by the marketer, and not of the overall population of each culture or country."

To date, the use of sample *matching* procedures, common in cross-cultural consumer research, is completely absent in the international diffusion literature[6]; see Table 2. In the context of diffusion studies sample *matching* essentially forces the researcher to make comparisons within comparable social networks to make valid statements on cross-cultural effects (or variances across countries). It should be emphasized that conceptually this is consistent with diffusion theory which suggests that diffusion processes are limited to social networks which will ultimately perceive the innovation,

[6] Some authors (e.g. Heeler and Hustad 1980) have suggested the external setting of the market potential in diffusion models which is similar to our, more general sample matching concept.

among other criteria, as being compatible with social norms or to be a relative advantage to existing substitutes (Rogers 1983). For example, 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.

In the next section we will define the four components that define a "diffusion pattern" and show how sample matching allows us to compare their variations across countries.

DEFINING A DIFFUSION PATTERN

We will now define the four components of a diffusion pattern that require *matching*. These components should be seen as the four basic sources of global variations in new product diffusion patterns. Component #1 is the social system size. Component #2 is the long run penetration ceiling. Component #3 is the first year acceptance level, or the intercept of the penetration curve, and Component #4 is the speed of diffusion between these two limits.

Component #1: Social System Sizes. We define social systems as populations within which innovations diffuse, and whose sizes vary from country to country in a fashion exogenous to the existence of the innovation itself. We label the social system size of country i, S_i. If the innovation is a consumer product, the social system size for each country may, for example, be estimated by its total population, among other variables. Variations in diffusion patterns, therefore, have a first source originating from exogenous variances in population sizes across countries: China with over 1 billion persons, versus Togo with less than 4 million persons, or Nauru with less than 10,000 inhabitants. For industrial products, analogous variables might be considered (e.g. number of hospitals for CAT scanning equipment). Of course, social system sizes may vary in time, which might be especially important for studies covering very long time horizons. As their absolute size, the dynamics of social system size are also considered to be exogenous to the innovation and the change agents' actions. Population growth rates, for example, are driven by demographic or other relevant models external to the diffusion process.[7]

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[7] Of course, if the innovation is designed to control social system dynamics, these effects would be added as a separate model to the exogenous forces identified.

Using the cellular telephone industry as an example, if we were to plot the absolute number of subscriptions, over time, across various countries, we might conclude that the United States, having the most subscriptions, is an "innovative" country. Clearly, we want to adjust such figures for the fact that the United States has a very large population, compared to, say, Sweden. The top graph, in Figure 1, displays temporal penetration patterns across a sample of countries for cellular telephone subscriptions. In order to plot the data in terms of "penetration" (as opposed to subscriptions), we are required to externally impose a matching definition of the relevant social system size. A popular measure in the cellular telephone industry is to define the "market" as the total population in the country, and to express penetration as "penetration per pop". The top figure is matched, therefore, in order to adjust for *social system size* using population. 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). From this graph one might also conclude that the Scandinavian countries are closer to saturation than countries in Southeast Asia (e.g. Thailand).

Component #2: Intrinsic Utilities: the Ceiling. Sample matching on social system size alone, however, is insufficient to fully describe the social network within which a product diffuses because a certain percent of individuals within a given social system may never have sufficient intrinsic utility for the innovation in question (Rogers 1983). This intrinsic utility can vary from one country to another (i.e. the armed forces of landlocked countries, though these may be large or small, may have no utility for nuclear submarines -- irrespective of how these are marketed). Rogers (1983) notes that for most innovations and irrespective of the change agents' (firms') actions, a certain percentage of the social system's population may never adopt the innovation in question. This is also reflected in the split-population hazard models advanced in Sinha and Chandrashekaran (1992). A high percentage of infants within each social system, for example, will not subscribe to cellular telephone services since the intrinsic utility for these over the "study horizon" will not be positive (while the current cohort of infants may eventually adopt as they grow older, they will be replaced by a new set of such infants). Because intrinsic utilities will be zero (i.e. irrespective of potential dynamics in income or substitution effects) for some portions of the population, we define an exogenous ceiling, C_i, which is independent of the size of the social system (i.e. small countries can have either large or small ceilings). For many expensive consumer products, considering the percent of households having a sufficiently large income will likely lead to appropriate ceilings. The intrinsic utility ceiling, therefore, is the second source of variation across countries. Of course, this ceiling may also be dynamic and change over time due to a variety of factors. Again, these factors are exogenous to the innovation itself (e.g. changes in income distribution over time, changes in literacy rates, etc.).

The bottom graph in Figure 1 illustrates penetration levels for the cellular industry when the populations are further matched across countries on their intrinsic utilities using 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".[8] A motivation for this definition is given later. 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. When contrasting the top and bottom graphs, we clearly see that "innovative" behavior under one definition appears less so under another, and high-growth markets are transformed into slow-growth markets when the definition of the social system ceiling is matched across countries. Innovative countries are no longer Scandinavian, but South-East Asian. In contrast to conclusions drawn earlier, it appears that Thailand may be closer to saturation than Scandinavian countries which have substantially lower penetration levels. This illustration clarifies that hypotheses and tests for variances across countries relating to the dynamics of adoption over time are wholly dependent on one's definition of the social system and intrinsic utility.

One could multiply C_i and S_i and call this a "market potential" or M_i; traditionally, M_i is often used as a single construct and internally estimated with sales data. There are a number of important reasons to view C_i and S_i as two separate concepts. First, S_i is a scale parameter; C_i on the other hand is an "intensity" parameter which is bounded ($0 \leq C_i \leq 1$), and measures not the scale of a social system, but rather the degree to which an innovation is compatible within the aggregate population. Keeping the two concepts apart allows, therefore, researchers to correctly attribute sources of variations. A second reason for separating C_i from S_i is that they represent fundamentally different processes (e.g. demographic models versus income distribution models). Seeing the two parameters as distinct forces allows the modeler to explicitly frame the problem within a diffusion paradigm. The two concepts should also be distinguished as they provide more detail to the modeler from which tests of external validity can be performed. In the unmatched approach, a market potential can be estimated, yet it becomes difficult to know if this number has external

[8]Data on these percentages are obtained from Euromonitor Ltd.

validity. With the matched approach, the study of growth dynamics can only take place after the acceptance of an externally valid and matched measure of social system and ceiling. We will see later that from a statistical point of view, the matched approach also generates a better and more plausible fit to the adoption data.

Component #3: Time Origin Intercept. Matching social systems and ceilings across countries is a necessary, but not sufficient, condition to make valid cross-country or cross-cultural comparisons of diffusion patterns. Times of origin must also be matched across countries to correct for the fact that product introduction timing may vary widely across countries: a third source of variation in adoption levels across countries. In the cellular industry, for example, Japan adopted in 1979 while the United States postponed their adoption decision until 1983. 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 2 for a graphical illustration) and result in severe biases and spurious interpretations. The reader will note that the time origins have been adjusted by the age of each system in Figure 1.

In addition to precluding an assessment of the impact of the introduction timing (delay) on subsequent penetration growth, a failure to ***match*** diffusion curves on time origins can also lead to left-hand truncation bias. Table 2 shows that many studies of international diffusion may suffer from these truncation biases. 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 estimates of early adoption levels (e.g. a country may be deemed "innovative" when, in fact, the observed level of adoption is inflated due to a truncation in the diffusion curve). To overcome these problems, diffusion curves must be matched using the first year of within-country penetration (i.e. after 12 months) as a time origin which is comparable across countries.[9] The time t, therefore, measures the number of years elapsed since the country has adopted the innovation ($t \geq 1$). Since the origin is put at $t=1$ (as opposed to $t=0$), we can define $n_{i,1}$ to measure the number of first-year adopters. The penetration curve's ***time of origin intercept*** is thus defined as A_{i1}, or $[n_{i,1} / C_i S_i]$; the number of adopters having purchased the product during the first year (or relevant time period)

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

divided by the matched social system adjusted for the matched ceiling.[10] It should be noted that this figure is similar but not identical to the innovation parameter of the Bass model. Rather it is a *variable* of given value for countries having at least one year of adoption. The first year penetration level is therefore an exact, directly interpretable, and unambiguous concept that can be compared across countries, provided that social system and ceiling are also matched across countries. As we discuss later, for countries which have yet to launch an innovation, we can provide plausible and theoretically justified estimates of A_{i1}.

Component #4: Growth Rates. The final source of variation across diffusion patterns is the growth rate, B_i, between the intercept and the ceiling. Growth is defined, therefore, as occurring only after the first year (i.e. if a product existed for only one year, then it did not grow. We will argue that growth rates cannot be co-estimated with the time-origin intercept, but only *after* this has been established. Because we have already matched on social systems, ceiling, and time origins, this growth parameter will also be directly comparable across countries.

From the above discussion one can see that matched approaches call for a sequential estimation of the model parameters rather than a simultaneous estimation. We will elaborate in detail on this estimation concept in the next section after the formal presentation of the analytic model.

AN EMPIRICAL MODEL

The Model

In this section, we propose a model which can assess the influence of exogenous and endogenous forces on the basic components of *within-country* adoption patterns. For a given country, *i*, we define the following time-series adoption function:

$$n_{i,t} = [(\frac{n_{i,1}}{C_i \; S_i}) + B_i \, (\frac{N_{i,t-1}}{C_i \; S_i})] \, [C_i S_i - N_{i,t-1}] \, , \; t = \{1, 2, \ldots\} \, , \tag{1}$$

where $n_{i,t}$ is the number of adoptions in time period t ($t \geq 0$), 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

[10] 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).

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_iS_i therefore measures the long-run social network within which the innovation diffuses (e.g. is analogous to the "market potential" in the original Bass model).[11] Again, the intercept of the penetration curve is defined as A_{i1}, *or* $[n_{i,1} / C_iS_i]$. In the *unmatched* literature, A_{i1} is typically interpreted as the "innovation coefficient" or "external influence" coefficient; its time origin is either not defined, or is equal to zero (as opposed to the end of period 1, in our formulation). This *matched* formulation has a number of advantages over *unmatched* approaches. First, A_{i1} is directly interpretable, is matched, and has therefore an unambiguous meaning across countries. In our model, A_{i1} can be interpreted, in an agnostic manner, as the penetration curve intercept which is endogenous to the social system. In this sense, it is also compatible with diffusion paradigms. Second, it can be directly calculated for all countries having at least one year of data (i.e. we need not have lengthy series, as is the case using *unmatched* approaches). Third, it is not co-estimated with other parameters. This allows the researcher to test, for example, whether new product growth, B_i, is a function of a country's intercept, or first year penetration level. Finally, B_i, is defined as the growth rate parameter between the intercept and the social system ceiling. Of the various components of the formulation, this is the only parameter requiring information generated by new product acceptance after the launch year.

To test theories governing cross-country variances in the diffusion patterns, we incorporate country-specific covariates into the various components of the formulation in Equation (1). To ensure that A_{i1}, and B_i lie between zero and one, the following logistic transformations are used:

$$A_{i1} = [1 + e^{-d_1X_i}]^{-1} \quad (2)$$

$$B_i = [1 + e^{-d_2X_i}]^{-1}, \quad (3)$$

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.[12]

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

[12]The linear form d_lX_i (l=1, 2) is used for simplicity. However, one can easily generalize (2) and (3) to more complex relationships $f_l(X_i)$.

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

$$n_t = [A + B * (\frac{N_{t-1}}{C * S})] [C * S - N_{t-1}] \tag{4}$$

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 (4), "+", "*" and "-" refer to element-wise operations. Hence, for example, the j-th element of $C*S$ is given by C_jS_j, and the j-th element of $[B * (N_{t-1} / C*S)]$ is given by $[b_jN_{j,t-1}/(C_jS_j)]$. This model is similar in spirit to that proposed in Gatignon et al. (1989), with the exception of the inclusion of the matched 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.

Model Estimation

We propose a staged estimation procedure for this general model which is logically consistent with the diffusion paradigm presented in the previous sections, and which provides manifestly superior insights to *unmatched* approaches. The method consists of three stages which must occur in the following sequence: (1) *external* estimation and validation of the exogenous social-system sizes and long-run adoption ceilings, C_iS_i across countries, (2) calculation of the intercept term, A_{i1}, which is exogenous to the subsequent growth process, and (3) *internal* estimation of each country's growth parameter, B_i, which is endogenous to the social system, the ceiling, and the time-origin intercept. The temporal order of the three stages reflects the evolutionary nature of diffusion 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 insights to *unmatched* approaches. The staged methodology also takes advantage of certain characteristics of Equations (1) and (4), and fully uses each observation, regardless of the temporal length or cross-sectional nature of the data available (i.e. even if a country has only one year of observations, that observation is fully used to explain cross-country variances in diffusion patterns). 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 and/or prior to diffusion curve inflection points. Finally, another advantage of the staged procedure is that the same covariate can be allowed to affect all four components of the diffusion process. *Unmatched* approaches are unable to allow this given that all parameters are estimated simultaneously. Introducing the same covariate several times in the same model typically generates severe multicollinearity.

Stage #1 involves the *external* estimation and validation of the exogenous social-system sizes and long-run adoption ceilings, C_iS_i across countries. While the external estimation of these two components has been treated above, Stages #2 and #3 merit further explanation.

Stage #2. The second stage involves calculating the first-year intercept, A_{i1}, 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_{i1} in Equation (1), and fix A_{i1} as the first-year penetration level: $A_{i1} = n_{i,1}/(C_iS_i)$. This property exists as long as the data are consistently matched with an identical origin and over the same discrete time interval for all countries (e.g. monthly, annually). Again, the calculation of A_{i1} 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_{i1} 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 its value as the intercept is already known and fixed by time period 2.

For countries where one does not have the first data point, one can derive an estimate (forecast) of A_{i1} using the logistic function in (2). 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_{i1}, 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_{i1}, and we no longer make use of the cross-sectional model to estimate this term for that particular country.

Stage #3. Having now obtained vector variables of intercept values, A, ceiling levels, C, and social system sizes, S, we can in Stage #3 estimate the pooled model (4). The third stage in the sequence requires an estimate of the growth rate, B_i. 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 (3). 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.[13] The parameters C_i, S_i and A_{i1} remain, of course, fixed in order to estimate B_i, even though the series may have several observations.

AN EMPIRICAL ILLUSTRATION TO THE CELLULAR TELEPHONE INDUSTRY

We will now apply the estimation procedure using the cellular telephone industry as an illustration. Throughout this discussion, various theories of diffusion dynamics were generated following the recommendations made earlier (i.e. following diffusion constructs). To a large extent, these are complemented with managerial perspectives from two firms: Ericsson Radio Systems, and AT&T. Considering the time frame between 1979 and 1992 proves useful as no country had yet passed a clear inflection point in their diffusion/penetration curves, and diffusion data existed for only about half of the countries of the world, with virtually all having only a few observations each (e.g. mostly one, two or three years).

Practical considerations

The requirement to use covariates which measure international differences across 200 countries leaves us with a limited set of independent variables (e.g. basic socio-economic characteristics). As a consequence, some of the factors which can potentially have an impact on diffusion may not be

[13]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_{i1i}), 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.

testable due to a lack of data (especially in lesser developed countries where statistics are scarce for a variety of topical areas). A practical solution to testing "global theories" is the use of globally representative proxies. In what follows, we illustrate the use of proxies which represent the intersection of three considerations: (1) support in the diffusion literature, (2) managerial relevance, and (3) data availability. These three criteria will inevitably be faced by applied diffusion researchers. Specifically, in our illustration, 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 (i.e. countries having similarities in industrial development).

Another issue that is inevitably faced by cross-cultural diffusion researchers is that the generated hypotheses must be tailored to the actual product category in question (e.g. forces affecting the diffusion of anti-malarial drugs will be fundamentally different from forces affecting the diffusion of marketing text books). These hypotheses, however, have to find their roots in the diffusion paradigm. Our hypotheses, therefore, have been motivated by extant theories of new product diffusion.

Stage #1: Social Systems and Ceilings (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.[14] 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

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

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 but rather the per minute service charge. 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). Alternative definitions of social system (e.g. based on the number of automobiles, all moving vehicles, etc.), were considered but not reported here as they either generated similar results, and were theoretically less appealing (e.g. all households).

Appendix A reports C_i and S_i for the 184 countries studied. For the sake of illustration, and since the time period studied is limited in duration, we report fixed values for C_i and S_i (though these may vary over time due to changes in demography and macroeconomics). 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_iS_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, however, does not guarantee that it will, in some way, reflect theories of diffusion. We used three criteria to validate the ceiling parameters: (1) managerial face validity, (2) correlation to theoretically appealing covariates and

(3) comparisons to naive models using simultaneous (unmatched) estimation methods. First, lengthy discussions were conducted with international marketing managers involved in the global tracking of cellular telephone subscriptions. These gave managerial face validity to the definition chosen. Second, in external tests the adoption ceiling parameter was found to be significantly correlated with theoretically motivated covariates. For example, it varies significantly with income per capita, 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 have already seen that the application of the *unmatched* traditional Bass model fails to give plausible market potential estimates across countries. We will now test the "statistical" face validity of the estimates of C_i and S_i using pooled models. Table 4 summarizes *naive* applications of the pooled diffusion model in order to compare internal *unmatched* versus *matched* external estimation of the social system and ceiling parameters. Model 1 can be considered the base-case *unmatched* model in that it internally estimates all parameters which are assumed constant across countries: i.e. 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 *matched* social-system size, S, but it internally estimates the *unmatched* "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 *unmatched* 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 A). This result shows that it is insufficient to *match* social-system sizes alone and let the model indicate a ceiling level. Imposing a "diffused-prior" estimate of C_i=1.0 for all countries, 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 further 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 *matched* externally prior to estimating other diffusion parameters. Even so, Model 4 provides a single *unmatched* 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.

Stage 2: Time-Origin Intercept (A_{i1})

In our example of the cellular telephone industry, we can *calculate* the *matched* time origin or first year penetration percent which is used as a *matched exact* estimate of the intercept parameter, A_{i1}, for those countries which have at least one year's experience;[15] the values for this variable are available for 74 countries and are reported in Appendix A with a "*" sign. 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 (2) incorporating the explanatory covariates.

Table 6 summarizes estimations of Equations (2) using two types of covariates: (1) exogenous covariates given in Table 5, and (2) endogenous covariates. Exogenous covariates cover a variety of constructs motivated by diffusion theory: income/poverty levels, ethnic homogeneity, population growth rates, numbers of population centers, numbers of competing cellular systems, and the extent to which a country was/is communist. Besides the exogenous covariates given in Table 5, we included two time-varying endogenous covariates that investigate the so-called "demonstration effect". The first covariate is the total number of countries that adopted by the end of each time period.[16] The second asks if a country's diffusion rate is faster if a larger number of "similar" countries have adopted previously (Gatignon and Robertson 1985). In our case, it was felt that

[15] In the cellular industry, measurement error can be assumed to be negligible.
[16] This variable was highly correlated with the country's adoption timing. Using this latter variable provided similar results to the ones reported in Table 6.

"similarity" is best based on industrialization so for each country, in each time period we calculated the number of countries among the country's World Bank Group that adopted the innovation. The World Bank system uses various factors to cluster countries into 9 industrial groups such as "highly industrialized, "oil exporters", "lesser developed", etc.

Table 6 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). The models support the notion that poverty (crude death rates), which acts as a cross-country proxy 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 results 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 also seems to decrease with the number of major population centers. Intuitively, the more centers to be covered by the network, the more difficult to provide ubiquitous coverage in the first year (e.g. in Belgium the whole population was covered in the first year of service, whereas in the United States, this process is much slower). Influences which are positively related to initial penetration levels include population growth rates (a proxy 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 and initial penetration levels, no endogenous covariate proved explanatory for the first year penetration level. This result was surprising given that the timing of launch was felt to act as a proxy for equipment prices (the more recent the system was launched, the lower the equipment prices); this effect was not supported by the data. 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.

Stage #3: Penetration Growth (B_i)

Table 6 also reports the estimated effects of the covariates on penetration growth (B_i). Crude death rates and the number of ethnic groups all have a negative influence on the diffusion growth 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. As with initial penetration levels, it appears that "innovative" countries' growth rates are not different from those of later adopters of cellular systems.

Using the retained models given in Table 6, and equations (2) and (3), Appendix A reports the matched estimates of A_{i1} and B_i for 184 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 robust, plausible and, hence, manifestly superior to those obtained using the *unmatched* approach (see Table 1). 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), and variances in the growth rate coefficient (from .001 to .705). Such low estimates for the later two diffusion parameters are infrequently seen in the extant literature which primarily uses data from industrialized countries and also frequently suffer from truncation biases.

CONCLUDING REMARKS

In contrast to earlier criticisms that diffusion models are "risky" and "misleading", our paper shows that diffusion models work well if they are estimated using appropriate *matching* procedures. We have demonstrated this conclusion by discussing sources of cross-country variations in diffusion patterns. By taking an alternative philosophical perspective, we propose a model and staged estimation procedure which provides insights which were not forthcoming using *unmatched* approaches. By applying *sample matching* and the staged estimation procedure, we can 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 1 in particular) reveals that the critical factor in explaining diffusion patterns across countries is the matched definition of social system size, S_i, and adoption ceiling, C_i, which must be externally *matched* and validated (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 social system sizes and long-run adoption ceilings across countries.

A limitation of the proposed approach exists for product categories for which social systems and ceilings cannot be defined (e.g. diffusion processes across trans-national cultures: religous or linguistic groups). We feel that for the vast majority of products, however, one can reasonably estimate social system sizes across countries. Ceilings are more difficult, but can be generated using one or more criteria (in case of uncertainty); furthermore, as products diffuse, modelers are free to change these definitions over time as more information becomes available. The model proposed has the primary advantage of allowing researchers to rigorously test various hypotheses, whether generated by academics 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 illustrated the application of our approach to the cellular telephone industry across 184 countries. Table 7 summarizes the results. First, we note that the impact of many factors (e.g. the effect of communism) is not uniform across the various components of diffusion. Other influences hypothesized in the diffusion literature have only marginal effect (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 diffusion; income per capita has a generally positive influence; crude death rates have a negative influence. We also find that endogenous influences are 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 actors 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. The proposed modeling framework is equally applicable to other categories.

Finally, we want to point out that our discussion has ignored the potential use of the proposed modeling procedures in forecasting exercises (as our contribution is focused on modeling, estimation and, to some extent, substantive theory testing). Though not presented here, for reasons of confidentiality, it is interesting to know that versions of the models presented here have been successfully used and externally validated over the past 8 years by cellular-telephone manufacturers to forecast within-country diffusion patterns (especially for countries which have not yet launched cellular services). Model-based projections are regularly used as benchmarks which are compared against or combined with forecasts generated from local (country or regional) offices.

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Table 1. Estimated Bass-Model Coefficients Across Countries using nonlinear Estimation

Countries	DF	External Influence a	P-Value	Internal Influence b	P-Value	Potential M	P-Value	Adjusted 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	5611	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	30981	1.00	-0.09
Bahrain	6	0.0000	1.00	-0.26	0.37	69253	1.00	-0.16
Belgium	6	0.0012	1.00	0.05	0.97	7325	1.00	-0.45
Bermuda	4	0.0003	1.00	-0.49	0.31	1884	1.00	0.65
Brunei	4	0.0000	1.00	-0.23	0.89	58587	1.00	-0.98
Canada	8	0.0000	1.00	0.30	0.30	-575682	1.00	0.79
Cayman Islands	6	0.0000	1.00	0.00	1.00	4472	1.00	-0.21
Chile	4	0.0000	1.00	0.45	0.63	108164	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	3505	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	-168234	1.00	0.44
Egypt	6	1.1538	1.00	0.32	0.50	410673	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	-381546	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	-82022	1.00	0.84
Ireland, Republic of	8	0.0000	1.00	0.44	0.50	-69748	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	2652	0.00	0.95
Kuwait	5	0.0000	1.00	-1.08	0.43	164216	1.00	0.08
Luxembourg	8	5.4044	1.00	0.41	0.17	56820	1.00	0.83
Macau	5	2.4262	1.00	0.38	0.80	313990	1.00	-0.07
Malaysia	8	0.0000	1.00	0.37	0.38	-391401	1.00	0.69
Malta	3	0.0008	0.00	0.12	1.00	1408	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	217279	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	519471	1.00	0.27
Pakistan	3	0.0020	1.00	0.07	1.00	1264	1.00	0.34
Philippines	6	0.0000	1.00	0.36	0.92	-62896	1.00	-0.30
Portugal	4	0.0000	1.00	0.28	0.70	316027	1.00	0.73
Saudi Arabia	11	-0.0006	1.00	-0.04	0.84	-3346	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	-3071661	1.00	0.79
Spain	11	-1.8815	1.00	0.77	0.00	-1319390	1.00	0.96
Sri Lanka	4	0.0000	1.00	0.00	1.00	10001	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	1688	0.95	0.12
Taiwan	4	-0.0009	1.00	0.28	0.93	-54539	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	-15459	1.00	0.27
Turkey	7	0.0000	1.00	0.49	0.21	196179	1.00	0.83
United Arab Emirate	4	0.0009	1.00	-0.16	0.88	13393	1.00	-0.54
United Kingdom	8	0.0560	0.26	0.27	0.55	1893	0.25	-0.05
United States	9	0.0094	0.08	0.67	0.00	14134	0.00	0.98
Venezuela	4	0.0000	1.00	4.37	0.60	156690	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**	**-61417**	**0.74**	**0.37**
Standard Deviation		**2.5832**	**0.32**	**0.72**	**0.37**	**471265**	**0.42**	**0.54**

Note: DF= degrees of freedom; figures are rounded

Table 2. Summary of Recent International Diffusion Studies

Study	Number of Countries	Sample Matching	Left-Hand Truncation Bias	Exogeneous Covariates	Endogeneous Covariates
Gatignon et al. (1989)	14	No	Yes	3	None
Heeler and Hustad (1980)	16	No	Yes	0	None
Helsen et al. (1993)	12	No	No	6	None
Mahajan and Muller (1994)	16	No	Yes	0	Yes
Takada and Jain (1991)	4	No	Partial	1	Yes
Present study	**184**	**Yes**	**No**	**8**	**Yes**

Table 3. 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%

Table 4. 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 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. Logistic Models of External and Internal Influences

Covariate	Origin Intercept Ai		Growth Rate Bi	
	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
R_a^2	0.67	0.68	0.9325	0.9326

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

Table 7. Degree of Covariate Influence on Global Diffusion Patterns: Strength and Direction

Covariate	Initial Penetration		Penetration Growth		Penetration Ceiling	
Exogeneous Factors						
Demographic Factors						
Aug. Annual Pop. Growth Rate	**	(+)	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	*	(+)	ns		*	(+)
Social System Factors						
No. of Ethnic Groups	**	(-)	***	(-)	ns	
Endogeneous Factors						
Proportion World Bank Countries	ns		ns		n/a	
No. of Other Countries Adopted	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. Penetration of Cellular Services, Across Countries

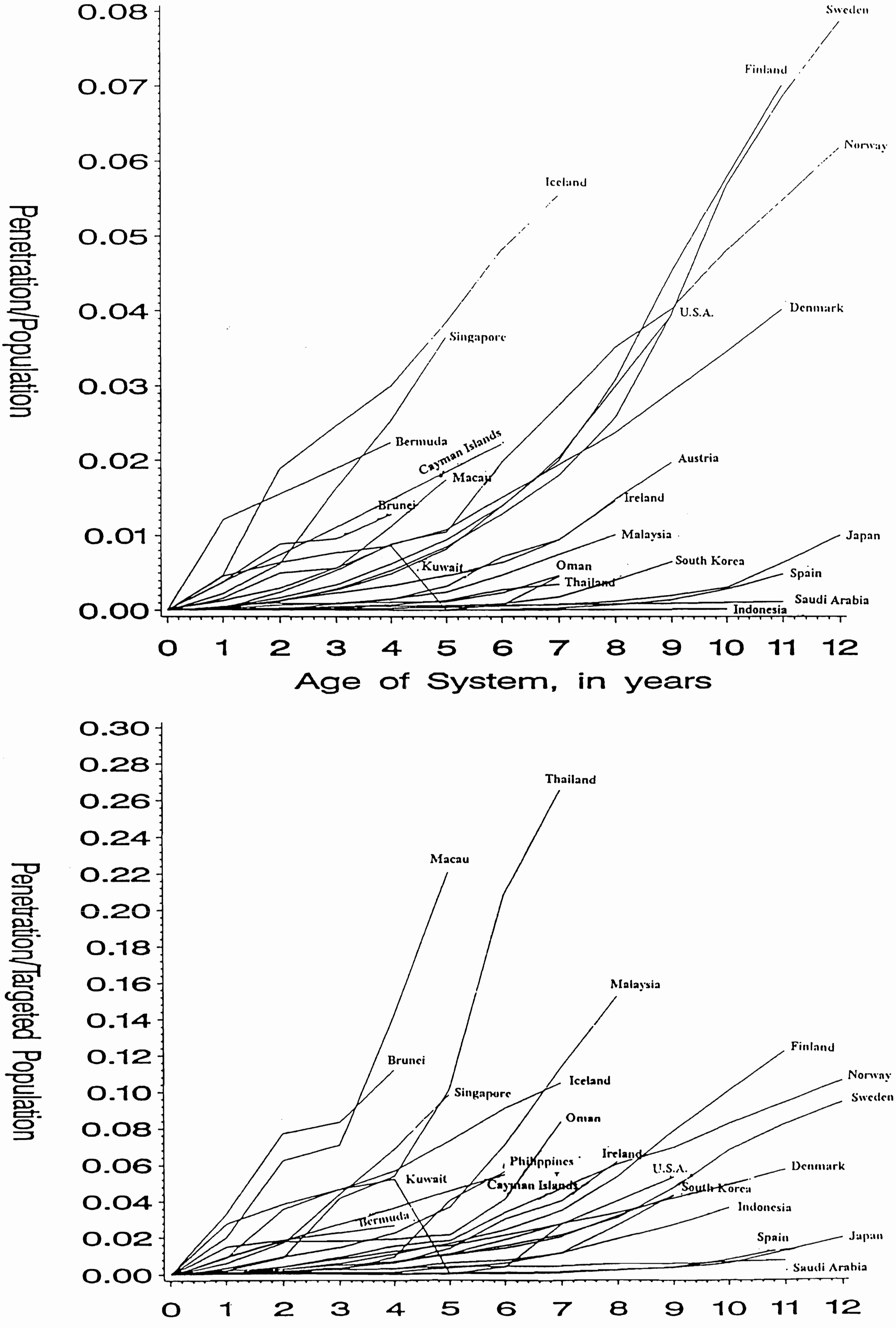
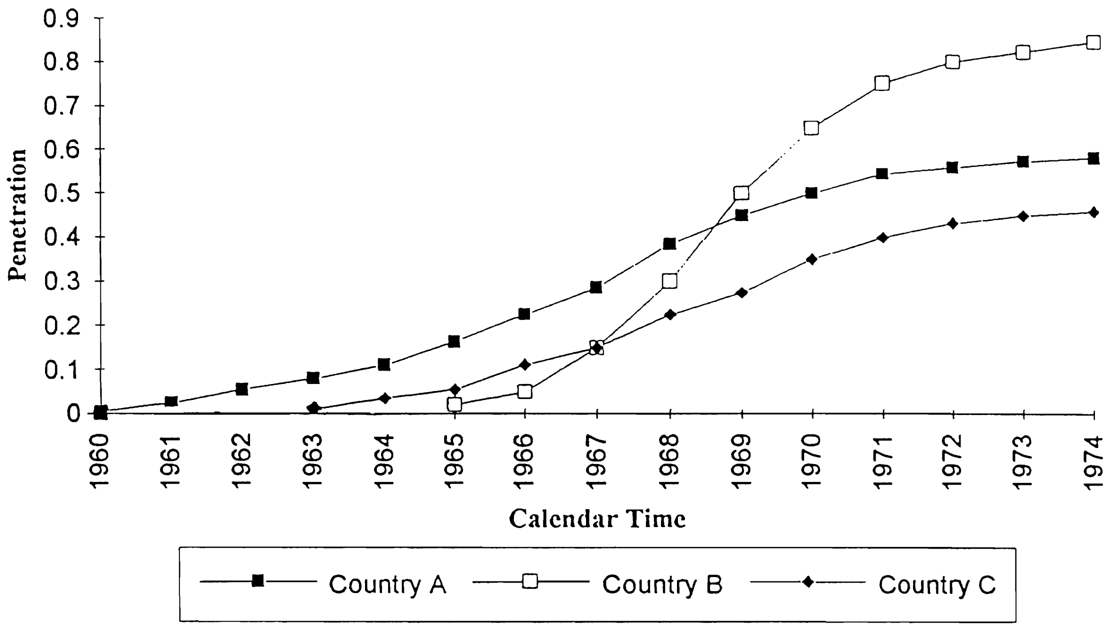
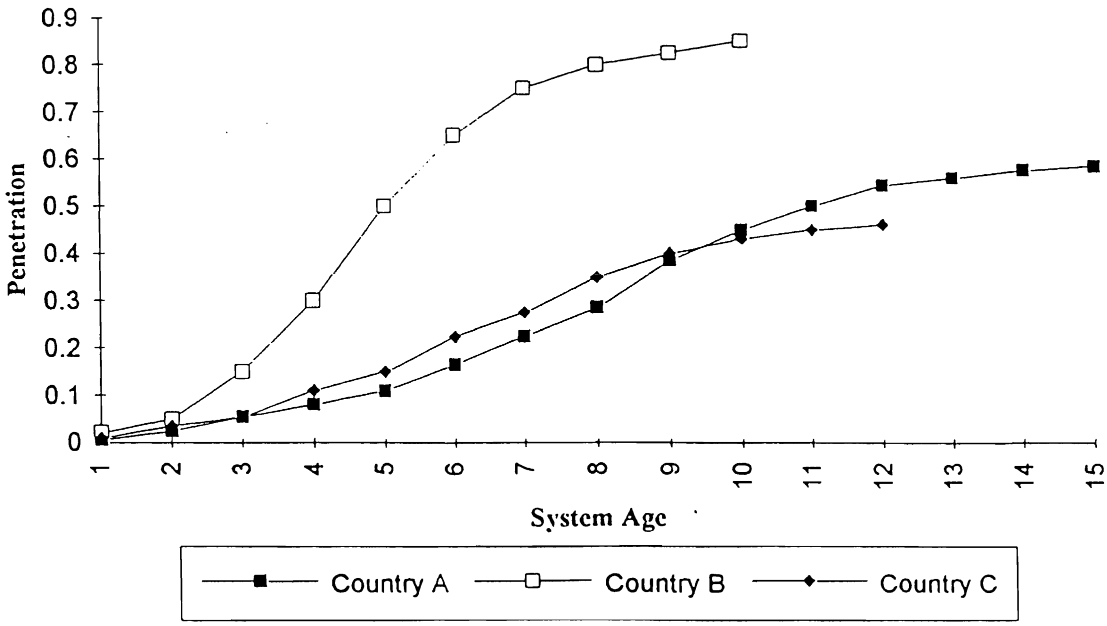


Figure 2. Left-Hand Truncation Bias

Diffusion curves not adjusted to comparable origin



Diffusion curves adjusted to comparable origin



APPENDIX A

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

	Country	Stage 1 Si (000's)	ci	ciSi (000's)	Stage 2 ai	Stage 3 bi
1	Afghanistan	16450	0.002	33	0.0001	0.004
2	Albania	3335	0.002	6	0.0048	0.402
3	Algeria	26022	0.032	833	0.0004 *	0.464
4	American Samoa	43	0.180	8	0.0079	0.458
5	Angola	8668	0.005	44	0.0001	0.003
6	Antigua & Barbuda	64	0.089	6	0.0050	0.266
7	Argentina	32664	0.105	3430	0.0004 *	0.164
8	Australia	17288	0.538	9301	0.00002 *	0.464
9	Austria	7666	0.459	3519	0.0005 *	0.144
10	Bahamas	252	0.368	93	0.0022 *	0.417
11	Bahrain	537	0.257	138	0.0123 *	0.427
12	Bangladesh	116601	0.002	175	0.0007	0.079
13	Barbados	255	0.299	76	0.0028	0.117
14	Belgium	9922	0.417	4137	0.0012 *	0.184
15	Belize	228	0.041	9	0.0054	0.275
16	Benin	4832	0.005	24	0.0010	0.010
17	Bermuda	58	0.836	48	0.0144 *	0.155
18	Bhutan	1598	0.012	19	0.0007	0.011
19	Bolivia	7157	0.024	172	0.0116 *	0.111
20	Botswana	1258	0.018	23	0.0005	0.217
21	Brazil	155356	0.076	11807	0.0010 *	0.462
22	Brunei	398	0.114	45	0.0331 *	0.274
23	Bulgaria	8911	0.200	1782	0.0007 *	0.083
24	Burkina Faso	9360	0.002	18	0.0002	0.017
25	Burma	42112	0.001	59	0.0006	0.046
26	Burundi	5831	0.001	8	0.0018	0.015
27	Cambodia	7146	0.001	7	0.0006	0.018
28	Cameroon	11390	0.005	58	0.0001	0.034
29	Canada	26835	0.668	17926	0.0013 *	0.491
30	Cape Verde	387	0.006	2	0.0055	0.074
31	Cayman Islands	27	0.406	11	0.0091 *	0.376
32	Central African Rep	2952	0.002	6	0.0002	0.006
33	Chad	5122	0.001	7	0.00003	0.002
34	Chile	13287	0.054	718	0.0079 *	0.389
35	China, People's Rep	1151487	0.005	5757	0.0001 *	0.230
36	Colombia	33778	0.073	2466	0.0019	0.444
37	Comoros	477	0.009	4	0.0052	0.030
38	Congo	2309	0.011	25	0.0005	0.035
39	Costa Rica	3111	0.123	383	0.0008 *	0.458
40	Cote D'Ivoire	12978	0.011	143	0.0011	0.064
41	Cuba	10732	0.050	537	0.0015	0.353
42	Cyprus	709	0.253	179	0.0072 *	0.104
43	Czechoslovakia	15725	0.221	3475	0.0010 *	0.159
44	Denmark	5133	0.702	3603	0.0018 *	0.167
45	Djibouti	346	0.022	8	0.0014	0.009
46	Dominica	86	0.039	3	0.0088	0.299
47	Dominican Republic	7385	0.029	214	0.0009 *	0.303
48	East Germany	16705	0.206	3441	0.0004	0.168